DISSERTATIONES RERUM OECONOMICARUM
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ALEXANDER GOFMAN

Experimentation-Based Product Development in Mature Food Categories: Advancing Conjoint Analysis Approach

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Supervisors: Professor Tõnis Mets (Ph.D), University of Tartu, Estonia

Professor Tiiu Paas (Ph.D), University of Tartu, Estonia

Opponents: Dr. Robert Kitt, Tallinn University of Technology, Swedbank, Estonia

Professor Marko Torkkeli (D.Sc.), Lappeenranta University of Technology, Finland

Professor Alan Brokaw (Ph.D), Michigan Technological University, USA

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I. Monographs or parts of monographs

Chapters in monographs

1. **Gofman, A.** 2009. Combining Eye Tracking with Experimental Design. In *Food Packaging Research and Consumer Response,* Moskowitz, H., Reisner, M., Lawlor, J., Deliza, R*.,* 230–246*,* Ames, Iowa: Blackwell Publishing. *[In Print]*.
2. **Gofman, A.** 2009. Getting the package and website graphics right with consumer co-creation. In *An Integrated Approach to New Food Product Development,* ed. Moskowitz, H., Saguy, S., Straus, T., 369–386, Boca Raton, FL: CRC Press / Taylor & Francis Group.
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9. Moskowitz, H., **Gofman, A.** 2007. *Selling Blue Elephants: How to make great products that people want BEFORE they even know they want them*. Philadelphia, Pennsylvania: Wharton School Publishing / Pearson Education.

[Translated editions: Arabic, Bahasa Indonesia, Chinese Simplified, Chinese Traditional, Dutch, German, English (India, reprint), Italian, Japanese, Korean, Lithuanian, Romanian, Russian, Spanish, Vietnamese and Thai]. Daily Bestsellers lists at amazon.com, amazon.uk and amazon.de in different sections; Selected by Executive Book Summaries as one of the Thirty Best Business Books of 2007; Selected as the Best Book in Product Development by ICFAI University Press; Selected in the Global list of the ten best business books of 2007 by the 'Business Magazin' (Romania)].

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10. Poras, J., Emery, S., Thompson, M. 2006. *Success Built to Last: Creating a Life That Matters.* Philadelphia, Pennsylvania: Wharton School Publishing/ Pearson Education. Acknowledged contributor to the World Success Survey chapter analyzing a conjoint analysis project, 222–254.
    [WSJ and BusinessWeek bestseller; Top 3 of Amazon's Best Books of 2006 Editors' Picks: Business].
11. Bevolo, M. 2009. *The Golden Crossroads: Multidisciplinary findings for business success from the worlds of fine arts, design and culture.* Basingstoke, UK: Palgrave Macmillan. Acknowledged contributor to the RDE Survey chapter analyzing a conjoint analysis project [Forthcoming].

II. Academic papers published in international journals

12. **Gofman, A.,** Moskowitz, H. Application of Isomorphic Permuted Experimental Designs in Conjoint Analysis. *Journal of Sensory Studies* (accepted for publication).
13. **Gofman, A.,** Bevolo, M., Moskowitz, H. Role of Corporate Leadership and Innovation Claims in Consumer Perception of Premium Products. *International Journal of Innovation Management* (accepted for publication).
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Packages with Eye Tracking. *The Open Food Science Journal,* 3: 62–74. (Available from http://www.bentham.org/open/tofsj).
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- *Food Quality and Preference* – BIOSIS, CAB Abstracts, Biology & Environmental Sciences, EMBiology, Elsevier BIOBASE, SCISEARCH, etc. ISI Journal Citation Reports Impact Factor: 1.796.
- *Food Service Technology* (currently *Journal of Foodservice*) – EBSCOhost, CAB Abstracts, Global Health, Nutrition Abstracts and Reviews, etc.
- *The International Journal of Innovation Management* – International Bibliography of the Social Sciences (IBSS).
- *International Journal of Pharmaceutical and Healthcare Marketing* – Cabell's Directory of Publishing Opportunites in Marketing, Electronic Collections Online, Inspec, Scopus, Zetoc (British Library).
- *International Journal of Technology Management* – SCI, Social Sciences Citation Index, ABI/Inform, Computer Science Index, etc. ISI Journal Citation Reports Impact Factor 2007: 0.356.
- *Journal of Consumer Marketing* – ISI Alerting Services, Academic Research, Current Citations Express, Emerald, e-psyche, Expanded Academic Index, Galileo, General Reference Center, etc.
- *Journal of Product And Brand Management* – Emerald, CPI Digest, EBSCO EJS E-Journals, The Marketing Report, ABI/INFORM Global (ProQuest), Thomson Reuters, etc.

- *Journal of Sensory Studies* – SCI, Index to Scientific Reviews, Psychological Abstracts, PsycINFO, SCOPUS, etc.; ISI Journal Citation Reports impact Factor: 0.773.
- *The Open Food Science Journal* – Chemical Abstracts, Directory of Open Access Journals (DOAJ), Open J-Gate, Genamics JournalSeek, etc.

Patent descriptions in the international databases (www.espacenet.com)

US Patents:

25. *System and method for performing conjoint analysis*. Publication date: 2005-08-11. Inventor: Moskowitz Howard R; **Gofman Alexander**. Applicant: Moskowitz Howard R; Gofman Alexander. EC: G06Q10/00B; G06Q30/00A. IPC: G06Q10/00; G06Q30/00; G06Q10/00. Publication info: US2005177388 (A1).
26. *A system and method for content optimization*. Publication date: 2002-01-17. Inventor: Moskowitz Howard; **Gofman Alexander**. Applicant: Novation Inc I. [US]. EC: G06F17/30W1F; G06Q30/00A; IPC: G06F17 / 30; G06Q30 / 00; H04L29/06. Publication info: WO0205136 (A1).

USSR Patents (partial list):

27. *Display unit*, Patent no: SU1714662 (A1), Publication date: 1992-02-23. Inventor: **Gofman Aleksandr Ya**. Applicant: UK VNII Gornoj Geomekhaniki Ma. Classification: G09G1 / 16G09G1 / 16G09G1 / 16. Application no: SU19884454549 19880705.
28. *Device for storage and displaying of seismic signals,* Patent no: SU1644061 (A1). Publication date: 1991-04-23. Inventors: **Gofman Aleksandr Ya**; Pesok Viktor Ya. Applicant: UK VNII Gornoj Geomekhaniki Ma. Classification: G01V1 / 30; G01V1 / 28G01V1 / 30; G01V1 / 28G01V1 / 28. Application no: SU19874282895; 19870713.
29. *Arrangement for spark-safe switching of power supply of transistor converter*, Patent no: SU 1559209 (A1), Publication date: 1990-04-23. Inventors: Lappo Pavel V; **Gofman Aleksandr Ya**; Berestetskij Aleksandr P. Applicant: UK VNII Gornoj Geomekhaniki Ma. Classification: E21F9 / 00E21F9 / 00E21F9 / 00. Application no: SU19884371698 19880104.
30. *Device for presentation of information*, Patent no: SU1573469 (A1). Publication date: 1990-06-23. Inventor: **Gofman Aleksandr Ya.** Applicant: UK VNII Gornoj Geomekhaniki Ma. Classification: G09G1 / 16G09G1 / 16G09G1 / 16. Application no: SU19874223472 19870407.
31. *Method and apparatus for automatic charging and discharging of storage battery*, Patent no: SU1450041 (A1). Publication date: 1989-01-07. Inventors: Chernomordik Grigorij A; **Gofman Aleksandr Ya**. Applicant: UK VNII Gornoj Geomekhaniki Ma. Classification: H02J7 / 04; H01M10 / 44H02J7 / 04; H01M10 / 44H02J7 / 04; H01M10 / 42. Application no: SU19874176590 19870108.
32. *Method of spark-proof power supply,* Patent no: SU1411516 (A1). Publication date: 1988-07-23. Inventors: Kogan Eduard G; **Gofman Aleksandr**

Ya; Didenko Valerij P; Kufman Aleksandr Z. Applicants: UK VNII Gornoj Geomekhaniki Ma.; Proizv Ob Sozdaniyu Vypusku Sr. Classification: E21F9 / 00E21F9 / 00E21F9 / 00. Application no: SU 19864131929 19861008.

33. *Apparatus for measuring time-related parameters of track circuit codes,* Patent no: SU1418153 (A1). Publication date: 8/23/1988. Inventors: Gofman Igor Ya; **Gofman Aleksandr Ya;** Belinskij Pavel N. Applicant: Artemovskaya Distantsiya Signa. Classification: B61L23 / 16; B61L23 / 00; (IPC1-7): B61L23 / 16.
34. *Arrangement for ensuring spark-safety of load,* Patent no: SU1366650 (A1). Publication date: 1988-01-15. Kogan Eduard G; Didenko Valerij P; Kufman Aleksandr Z; **Gofman Aleksandr Ya.** Applicant: Proizv Ob Sozdaniyu Vypusku Sr; UK VNII Gornoj Geomekhaniki Ma. Classification: E21F9 / 00E21F9 / 00E21F9 / 00. Application no: SU19864107886 19860521.

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Optimizing a Political Platform as if a Consumer Product. In *Proceedings of 2000 ESOMAR Net Effects*[3] in Dublin, Ireland (CD).

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Conference Presentations

65. **Gofman, A.** 2009. The Future of the Web. *14th Annual CASRO Technology Conference*, New York, May 2009.
66. **Gofman, A.** 2009. Mind Genomics. *UPSHOT/BrainJuicer Conference on Memes, Messages and Media*, Chicago, April 7, 2009.
67. **Gofman, A.** 2009. From Combinatorial Innovation to Mind Genomics. *McCANN-ERICKSON/BrainJuicer Conference on Memes, Messages and Media*, New York, April 2, 2009.
68. **Gofman, A.,** and Moskowitz, H. 2008. From Optimizing Online Research To Optimizing the Web through Researching: Emerging Research Methodologies and Web Analytics in Web 2.0 Universe. *13th Annual CASRO Technology Conference*, New York, June 2008.
69. **Gofman A.** 2007. Advancing Multivariate Landing Page Optimizations with Rule Developing Experimentation. Presentation at *2007 eContent Summit: Scenarios for the Futur*e in Brioni, Croatia. *[Opening Speech].*
70. **Gofman A.** 2007. Rule Developing Experimentation. Presentation at *NYU Alumni Conference "New Directions in Marketing Intelligence"*. NYU Stern School of Business, November 16, 2007.
71. **Gofman, A.,** and Moskowitz, H. 2004. State of the art research and development tools to put innovation in the hands of the many. *The XV ISPIM Annual Conference*, Oslo, Norway.
72. Marketo, C., **Gofman, A.,** and Moskowitz, H. 2004. A new way to estimate interactions in conjoint analysis. *2004 7th Sensomentrics Conference*, Davis, CA.

V. Other publications

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73. **Gofman, A.** 2009. Infographics and Data Visualization. *Research World.* (Accepted for publication in 2009).
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88. **Gofman, A.** 2009. Pay per e-mail system would sound the death knell for spam. *Daily News and Analysis*. February 21, 2009, Corporate section.
89. **Gofman, A.** 2008. Presaging the Changes the World Wide Web will Spin for Itself. *Daily News and Analysis*. December 3, 2008, Corporate section.
90. **Gofman, A.** 2008. The High Land of Opportunity. *Daily News and Analysis*. August 28, 2008, Management and Marketing section.
91. **Gofman, A.** 2008. The president as a food product. *Daily News and Analysis*. May 22, 2008, Management and Marketing section.
92. **Gofman, A.** 2007. Lessons from HP's 'Always-On' Intelligence system. *Daily News and Analysis*, December 27, 2007.
93. **Gofman, A.** 2007. How to Defeat Murphy's Law in the Stock Markets. *Daily News and Analysis*, November 29, 2007.
94. **Gofman, A.** 2007. Consumer research and the curse of the rear view mirror, *Daily News and Analysis*. November 1, 2007.
95. **Gofman, A.** 2007. Consumers know what they want. Or do they? *Daily News and Analysis*, October 4, 2007, Management and Marketing section.

INTRODUCTION

List of papers

The thesis is a collection of three original publications. The particular publications are referred to in the text below by their respective Roman numerals.

I. **Gofman, A**. 2006. Emergent Scenarios, Synergies, And Suppressions Uncovered within Conjoint Analysis. *Journal of Sensory Studies*, 21(4): 373–414.

II. Moskowitz, H., **Gofman, A.,** and Beckley, J. 2006. Using High-Level Consumer-Research Methods to Create a Tool-Driven Guidebook and Database for Product Development and Marketing. *Journal of Sensory Studies*, 21(1): 54–100.

III. **Gofman, A**., and Moskowitz, H. 2009. Steps towards a consumer-driven innovation machine for 'ordinary' product categories in their later life-cycle stages. *International Journal of Technology Management,* 45(3/4): 349–363.

Actuality of the Dissertation and Current State of Art[1]

In the last decades, consumers are increasingly involved in innovation process, a major driving force of business success. Research of von Hippel (1986, 1988, 2005) and von Hippel and Katz (2002) points to the critical importance of this involvement for innovation, particularly in product development. Sanchez and Mahoney (1996), Berghman, Matthyssens, and Vandenbempt (2006), Gold, Malhotra, and Segars (2001), and Möller (2006) demonstrate that utilization of the consumer and market knowledge can lead to an increased effectiveness of innovation process.

The innovation facilitated by organized and structured information about the market and the consumer is a vital resource to business success, argue Inkpen and Dinur (1998), and Li and Calatone (1998). As Drucker (1995) pointed out, "…knowledge has become the key economic resource and the dominant – and perhaps even the only – source of competitive advantage… Such knowledge includes, but is not limited to, knowledge about one's company, industry, competitors, customers..."

In his works, von Hippel (1976, 1978, 1986, 1988, 2005) demonstrates that a key to success is in consumer knowledge driven innovation. The research conducted in Hurley and Hult (1998), Calantone, Cavuşgil, and Zhao (2002), De Luca and Atuahene-Gima (2007), and Walter, Lechner and Kellermanns (2007) further proves the importance of such knowledge accumulation, re-use and transfer for driving innovation.

[1] Specific terms used in the dissertation are explained in the Dictionary of Terms

Analyzing consumer-driven knowledge for businesses, scholars such as Deshpandé and Zaltman (1982), Davenport and Klahr (1998), von Krogh (1998), Arnett, Menon and Wilcox (2000), and De Luca and Atuahene-Gima (2007) conclude that this knowledge represents a firm's resource and has the potential to affect a firm's marketplace position.

Ruggles (1998), Shin, Holden and Schmidt (2001), Schlegelmich and Penz (2002), Beckley (2007) confirm these findings based on the analysis of multiple commercial implementations. In a recently released worldwide IBM study, the majority of the executives reported that that pay extreme attention to understanding consumers preferences for product development and other aspects of business. This in turn points towards even deeper involvement of consumers into the process resulting in the development of the 'prosumer' – a consumer/producer who is extensively integrated into the value chain to facilitate more precise customization of the production processes. The consumer-driven knowledge, concludes IBM (2008), is critical there.

Although in some specific situations profitable improvements do not require extensive research (Mets, 2006), in the majority of cases, argue Drucker (1998) and Senge (1998), innovations result from a conscious, purposeful search for innovation. This is particularly critical during *New Product Development (NPD)* stage, as pointed out by scholars such as Hunt (2000).

NPD and related business processes are progressively more important in the knowledge-based economy. Hunt and Morgan (1995) points that scholars and increasingly companies acknowledge the significance of NPD in developing competitive advantages over their rivals. Leonard-Barton (1992), Olson, Walker and Ruekert (1995), Cooper and Kleinschmidt (1995), Hunt (2000), McDonough, Kahn and Barczak (2001), Goffin and New (2001), Belliveau and Griffin (2002), Wood and Otto (2006), Trott (2008) progressively build the notion that fast, efficient, targeted and disciplined innovation in NPD is crucial for economic success of the modern enterprise because it allows firms to occupy marketplace positions of competitive advantage. That, in turn, argue Ayers, Dahlstrom and Skinner (1997) and Hunt (2000), results in firms improving their financial performance.

According to Riquelme (2001), Sherman, Berkowitz, Souder (2005), and Thomke (1998, 2001, 2003), new product launches are a key driver of business growth. Jaeger et al. (2003) argues that in today's business environment, a continuous supply of novel products is essential to retaining competitive advantage. In the reality, argues Flavin (2008), a majority of the new product launches fail. Across industries, the failure rate for new product launches ranges from an estimated 50% to 75% (Ibid). The rate of success in the food industry is lower than in industrial sectors. Goldman (2005) elaborates that regardless of the companies' intent to bring innovative food products to the market, the majority of the new launches are just replication of the competition. This in turn results in the new food products failure rate of approximately 72%-88% as reported in Buisson (1995), Rudolph (1995) and Lord (1999). Fuller (1994) estimates that for each food product that goes into test market, thirteen products are developed in laboratories and tested before being rejected.

A 1997 study (Frozen Food Digest, 1997) shows that the failure rate for new product introduction in the US retail grocery industry is 70–80 percent. The U.S. "Top 20" food companies enjoy a 76 percent success rate for their new product introductions while the "Bottom 20,000" U.S. food companies have only an 11.6 percent success rate for new product introductions. A major difference between the Top 20 new product introductions and Bottom 20,000 introductions is the apparent lack of consumer research, experimentation and strategic marketing done by the Bottom 20,000 (Ibid).

According to Costa and Jongen (2006), radically new products on the European food markets are rare (only 2.2 percent of total product launches), dropping down from an estimated 7–25 percent range in the late 90s as reported in Lord (1999) and Rudolph (1995). The European food and beverage industry exhibits a lower research and development (R&D) investments than industries in other sectors and is quite conservative in the type of innovations it introduces to the market. Avermaete et al. (2004) estimates that an estimated 77 percent of total European product launches have no novelty at all or possess an incremental level of novelty only. This approach to innovation, which keeps R&D costs low and implies a diminutive technological risk only, does allow the introduction of a relatively high amount of different products in a short period. The large majority of food products developed in this way cannot, however, be considered truly new (Galizzi and Venturini, 1996). Moreover, argue Grunert, Baadsgaard, Larsen and Madsen (1996) and Trail and Grunert (1997), with mere technology-based reductions of processes' and ingredients' costs being frequently marketed as new, enticing benefits to the consumer, it becomes increasingly harder for buyers to perceive the added-value of 'slightly new' food products and thus reward incremental innovation.

Some of the reasons behind the high new food product failure rates, points Garcia et al. (2007), are related to the utilized NPD process. Kärkkäinen, Piippo and Tuominen (2001) and Stewart-Knox and Mitchell (2003) noted that whilst a wide range of product development process factors are known to influence product success and failure, these predictors are based almost exclusively upon investigations into industrial rather than food products. Fernandez and Gomez (2005) argues that the complexities surrounding the NPD process in food industry are exacerbated by the market characteristics as food markets are mature and overall volume growth is fairly static in size and arguably in value. Harris (2002) observes that some food categories are nearing product saturation with too many products, especially line extension, which can confuse consumers.

Socio-economic and technological developments of the last decades in Western society have impelled a shift in the food industry orientation from production to market. Analyzing the trend, Grunert et al. (1996), Meulenberg and Viaene (1998), Traill and Meulenberg (2002), and Costa and Jongen (2006) argue that from the economic perspective, the increase of disposable income and the decrease in population growth resulted in the deceleration of the demand for food in developed countries. Meanwhile, the scientific and technological developments of the last half-century gave rise to global-scale food production and distribution, making food supply almost enduringly and ubiquitously available in the Western World (Putnam, 2002). One critical corollary of this process, conclude Meulenberg and Viaene (1998), and van Trijp and Steenkamp (1998), is that this imbalance between supply and demand decreased the importance of availability and price as determinants of food purchase and increased the relative importance of *consumers' choice* criteria. Nowadays, most Western consumers can buy exactly what they covet to eat, instead of only what is available or affordable. Thus, the consumer became the driving element of the food chain.

Galizzi and Venturini (1996) argues that the major hurdles to innovation in food industry are persistent notions that eating preferences change slowly and that consumer avers to excessively novel food. These notions impact corporations' willingness to do in-depth and timely consumer research. At the same time, Prescott et al. (2002) and Moskowitz et al. (2005) list mounting evidences that consumers' food consumption behavior does change. In addition, consumers widely differ in their food preferences, as proven by Grunert et al. (1996) and Rabino et al. (2007). Grunert et al. (1996) and Trail and Grunert (1997) conclude that this presents an opportunity for the global food markets today resulting in innovation becoming more of a necessity than an option.

Garcia et al. (2007) and Beckley (2007) continue building on this notion demonstrating that market opportunities still exist for the innovating food companies that are prepared to respond to changes in consumer demand and food-related lifestyles. Developing new products and being innovative requires companies to have a deep understanding of the consumer, the market and the environment in which they operate but most importantly to effectively apply this knowledge to the development of new products that meet consumer's expectations. Beckley (2007) calls for the implementation of an effective, structured and consumer-oriented NPD process.

Reid and de Brentani (2004), and Flores et al. (2003) associate innovation with a poorly defined *fuzzy front end* where experimentation with consumer perceptions is one of the most efficient ways of 'detecting the signal'. Moenaert, De Meyer, Souder, and Deschoolmeester (1995), then Khurana and Rosenthal (1998) and Troilo (2006), argue that consumer research should be put in the center of the innovation function throughout the process.

One of the ways towards reaching such goals is utilizing *experimentation,* which, argue Thomke (2001), and Kahn, Barczak and Moss (2006), is at the very heart of NPD and thus is connected to corporate values, habits, strategies, and organizational structures. Thomke (2003) further points out that experimentation as an essential part of NPD and new product launches came under scholarly scrutiny only recently. Thomke (2001, 2003) also point to the importance of doing the experiments fast, quoting Edison saying that real measure of success is the number of experiments that can be conducted in

24 hours. Although it is an extreme opinion, it underscores the increased pressure of the competitive environment.

This business need to improve and compete through experimentation facilitated a range of approaches many of which are inactionable due to their complexity or time requirements or insufficient involvement of consumer-driven knowledge and preferences. While some of the existing experimentation methods are based either on a random or subjective selection of the objects of the experiments, others are lengthy and complicated (as adaptive experimentation described in Sasena et al. (2005)) and do not create actionable directions.

There are two competing approaches to experimentation: unstructured and structured. Ziman, (2000) and Trott (2008) argue that despite massive theoretical work, corporations frequently use mainly unstructured experimentation in NPD. Research of noted scholars from Wharton School of the University of Pennsylvania and University of Texas, Wind and Mahajan (2001), analyzes the use of unstructured experimentation at Seiko, which develops over 2500 watch designs every year and introduce them to test markets. The successful prototypes are further fine-tuned, retested and then launched in the target markets. Belson (2003) further researches the applications of this approach to mainly unstructured experimentation at Sony, which develops, tests, and measures about 1500 product prototypes annually. About 20% of them are completely new designs, and only a portion of those find their way to the global market. This massive scale of mainly unstructured experimentation is feasible, according to Balasubramanian, Krishnan and Sawhney (2001), due to the declining cost of prototyping that encourages multiple prototyping but not necessarily based on disciplined experimentation.

At the same time, Dahan and Mendelson (1998, 2001), and Balasubramanian, Krishnan and Sawhney (2001) present mounting evidences that a structured and systematic experimentation is more efficient. This resonates well with Thomke (1998, 2001, and 2003) that demonstrate methods to lower the high cost of experimentation in corporations as a way to stimulate innovation. Thomke's works argue that new technologies facilitate experimentation making it easier than ever to conduct complex experiments quickly and inexpensively. The expanded use of experimentation provides an opportunity to take innovation to a new level. At the same time, Thomke (2001) stresses the importance for corporations to be willing to rethink their R&D from the ground up. In turn, conclude Beckley et al. (2007), and Kantowitz, Roediger, and Elmes (2008), this increases the usage of testing which is based on *researching consumer preferences on the concept level*. A research conducted by Dickinson and Wilby (1997) suggests that in many cases, such as product line extension, effective concept tests do not even require product trials. Further developing the field, Lees and Wright (2004) finds that respondents' answers to attitude and purchase intent questions show only minor variation with different formulations of the concept test statement while the ranking of the concepts shows no substantial changes across the different formulations. Therefore, the authors conclude, the type of concept statement formulation may not be that important, at least for early ranking tasks performed before experiential prototypes are available, thus opening the door to a wider usage of concept testing. This direction is supported in Moskowitz et al. (2005), Sinkula, Baker and Noordewier (1997), and Rabino et al. (2007), which advocate for an innovation at the concept level (as oppose to physical prototyping) that is knowledge-based with a disciplined development strategy, that aims to simultaneously create, understand, and database.

Millett (2006), and Klink and Athaide (2006) criticize some methods of obtaining consumer preferences pointing to the problem that consumers frequently cannot articulate exactly what they need, want, or like if asked directly. Agreeing with such arguments, Green and Wind (1973), Riquelme (2001), and Hauser and Rao (2003) point out that it is very difficult for consumers to articulate their needs and desires and researchers have to use other means to understand their motivations. Some arguments, such as presented in Kiley (2005), and Perera (2006), go as far as concluding that focus groups could not create a reliable direction for NPD or message optimization. Krieger et al. (2004) points to a solution for this problem – presenting consumers with a set of experimentally designed concepts. Research shown in Moskowitz et al. (2005) proves that it is much easier for consumer to choose a preferred option from a set of concepts.

Haagedoorn (1996), Nooteboom (1999), Soumodip (2007), Fagerberg (2006), and Langlois (2004) define innovation as the creation of the new or the re-arranging of the old in a new way in form of *combinatorial innovation*. Drawing on the theoretical works of Joseph A. Schumpeter, the idea of combinatorial innovation has been further developed by Usher (1954), continued by Hounshell (1984), and later on, by Weitzman (1998) who introduced the notion of 'recombinant growth'. According to Varian, Farrell and Shapiro (2004), "All the components are floating around in the broth, bumping up against each other and creating new molecular structures, which themselves become components for future development". Varian (2003) demonstrates the advantages of one research-based process of such combinatorial innovation – a systematic recombination of R&D-meaningful features. The process is more actionable under the guidance of the consumer preferences, argues Rabino et al. (2007), and must be based on an experimental design, rather than being random. Unfortunately, points out, Dobusch (2007), there is not much work done in the field to research the approach.

Dahan and Srinivasan (2000) summarizes that there is a need for low-cost, effective and reliable testing of new product concepts. Trott (2008) supports the idea for a need for a systematic and disciplined approach to NPD.

Conjoint analysis represents one of the major tools in concept development. It is an integral part of the experimentation-based prototyping on the concept level, increasingly used in NPD. Conjoint analysis, first introduced forty years ago in Luce and Tukey (1964) and further developed in Krantz, Luce, Suppes, and Tversky (1971), deals with a proposed set of axioms by which one can establish utility values for components based upon responses to combinations of these components.

Conjoint analysis is known for being a research technique by which one can investigate combinations of features to identify the predicted consumer preferences. Green and Rao (1971) drew upon the conjoint measurement theory, adapted it to the solution of marketing and product-development problems, considered carefully the practical measurement issues, and initiated a flood of research opportunities and applications (Wittink, and Cattin, 1989). Further developed and customized by Paul Green and his colleagues at Wharton School of the University of Pennsylvania (Green and Srinivasan, 1981, 1990a, 1990b, Wind, Green, Shifflet and Scarbrough, 1989; Green and Krieger, 1991, 1996), conjoint analysis has evolved into a mainstay of the research profession, and is a technique widely used in high profile products to design cars, hotels, lines of consumer products and others (Rosenbaum, 1987; Hauser, and Rao, 2003; Toubia, Simester, Hauser, and Dahan, 2003; Krieger, Green and Wind, 2004; Orme, 2006). Moskowitz et al. (2005), Rabino (2007), Beckley (2007), and Lee et al. (2007) extended the applications of conjoint analysis to food products.

Green and Srinivasan (1990a, 1990b), Green and Krieger (1991) argue that conjoint analysis has multiple advantages in quantifying consumer preferences. It assumes that a product or service can be described as an aggregate of its conceptual components: *attributes* (also called *variables, silos or categories*) and *elements (levels)* (Krieger et al., 2004; Moskowitz et al., 2005). By presenting a series of concepts, which are combinations of elements from different attributes, to a number of respondents and finding out which are most preferred, conjoint analysis allows the determination of utilities of each of the elements called the individual utility scores (part-worth or impact scores) of elements (Kessels et al., 2008).

Besides the individual contribution of the elements, some specific pair-wise combinations might have an additional impact on consumer liking or purchase intent. Green and Devita (1975) and Carmone and Green (1981) pointes out on the importance of researching such situations, which are called *interactions,* and estimating their utility scores.

Estimating pair-wise interactions among *continuous* variables (e.g., sensory attributes) is a relatively straightforward statistical issue as demonstrated in Porretta et al. (1996), Sundberg (2000) and Martens, Brediea, and Martens (2000), and Harrell (2008). Conjoint analysis works with *discrete* elements and thus introduces a new level of complexity into the issue of pair-wise interactions. The task of estimating interactions has been a point of research for a number of scientists (Green, 1973; Hayduk, and Wonnacott, 1980; Aiken and West (1991); Carroll and Green (1995), and Ping (1995). Ross and Creyer (1993) suggests that the determination of a synergistic effect between two elements (e.g., features of a product in NPD) to create a net effect significantly larger than seen by measuring each alone would present a clear opportunity to increase product acceptance through a combination of the two elements. Conversely, if two elements in combination work exceptionally poorly, knowledge of this negative effect as early as possible in the NPD would prevent the appearance of these suppressive combinations.

Chrzan and Orme (2000) points that simple methods for conjoint analysis ignore interactions on the premise that they are contained within elements yet not estimable. First Green (1973), then Green, and Devita (1975), Green and Srinivasan (1990a, 1990b), followed by Aiken and West (1991), Carroll and Green (1995) and Ping (1995) introduced increasingly more complicated methods, that partially addressed the issue of testing a limited set of interactions. Campbell and Stanley (1966), and Aiken and West (1991) suggest that a straightforward approach for estimation of all possible interactions – two-factor, three-factor, and so on – would call for a full factorial design with at least two replications per cell. For realistically sized problems relevant to NPD, the number of combinations generated would be prohibitively large for respondent evaluation. According to Evgeniou, Boussios, and Zacharia (2002), estimating of all interactions using the existing approaches is so computation intensive that it might need utilization of special high-performance support-vector computers usually found in artificial intelligence area. This points to a need for an easy and reliable method to estimate how pairs of product features interact to drive consumer interest.

As defined in Atkinson and Bailey (2001), and Hunter and Hunter (2005), *Experimental Design* as a statistical plan that lays out the combinations of the concept elements. It is a foundation of conjoint analysis, as well as several other experimentation-based approaches. In the traditional approaches, a single experimental design is applied to a set of variables only once creating a single design for all respondents (sometimes randomized). In addition, criticizes Moskowitz et al. (2005), the traditional experimental designs utilize complete concepts approach in which all features of the product are included in every concept.

Conceptual map of the existing conjoint-based consumer driven approach to product development is shown in Figure 1. The limitations of the existing approaches to experimental design are severe interlinked statistical problems in the analytic phase:

- Skewed Results. Limited number of concepts could skew the outcome as elements appear in a limited number of combinations and a few potentially very strong elements might distort the results (Rabino et al., 2007).
- Insufficient variation of combinations also prevents detection and estimation of interactions (pair wise and higher order) (Moskowitz et al., 2005).
- Collinearity. Complete concepts do not allow estimating the absolute utility scores of concept elements due to multicollinearity (Krieger et al., 2004).

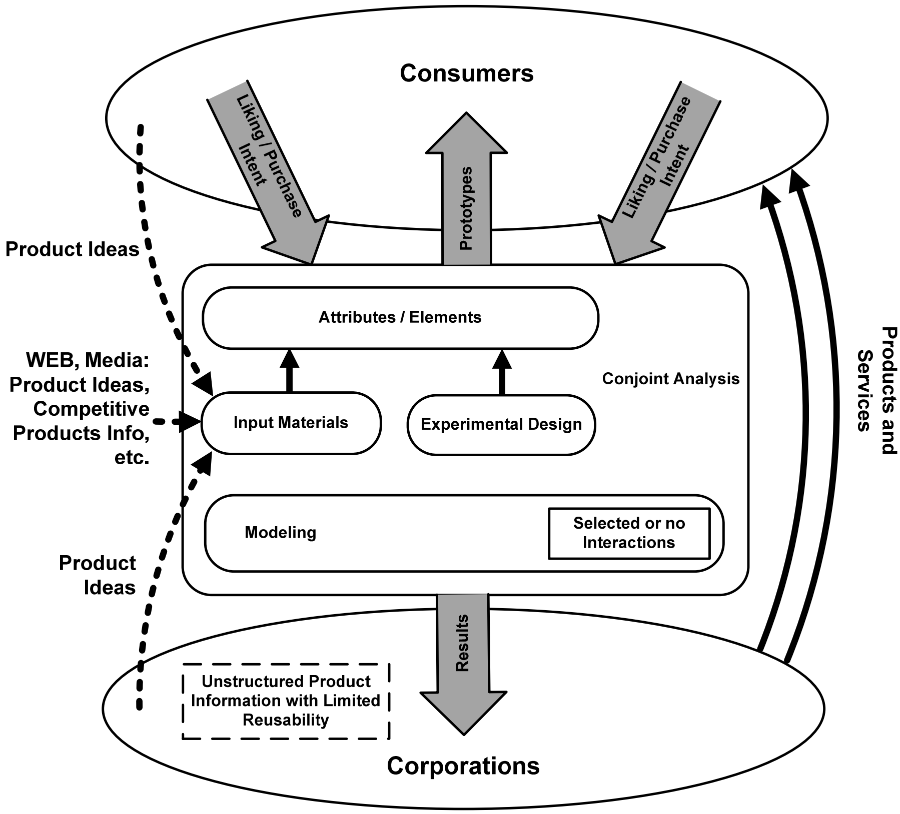

Figure 1. Conceptual Map of the conjoint-analysis based consumer-driven approach to product development. (Source: created by the author as generalization of many sources such as Krieger et al., 2004; Moskowtiz et al., 2005.)

- No True Estimate of the Basic Level of Interest. The statistical analyses of such complete concepts require effects model regressions, in which there is no estimate of the additive constant (the basic level of consumer interest), and the requirement that the utilities of the elements in each attribute add up to zero (Beckley and Moskowitz, 2002).
- No True Estimate of the Utility Scores of the Individual Elements. The requirement of the constant sum equal to zero means that if a new element is introduced into the study, the utilities of the other elements must be readjusted because they have relative value. This readjustment means that one cannot use the results for re-using and databasing (absolute values of the utilities that could not be easily, if at all, compared across the attributes or projects) (Beckley et al., 2007).

The process starts with gathering initial ideas (features of the product, related emotional messages, pictures of components). Arnett and Badrinarayanan (2005) demonstrates sources of ideas inside corporation such as brainstorming, CRM data, or ideation. In addition to traditional focus groups, Oreilly

(2007) specifies Internet as a new source of product ideas, especially blogs and other venues afforded by Web 2.0. Anderson (1998) researches word of mouth (WOM) campaigns as a possible source of ideas. The initial ideas are formatted into concise descriptive short sentences or other media creating individual elements (features of products) grouped into attributes of similar features. For example, attributes and elements for a new cookie products could be (the elements are bracketed and follow the attributes): "Flavors" ("Chocolate flavored; "Orange flavored", "Strawberry flavored"); "Size" ("Byte-sized"; "Oversized", "Normal size"). The elements could be more descriptive and be presented in a textual or graphical way.

Due to the limited number of variations in the concepts, the reliability of all data could be affected by a few strong elements. In addition, the existing approaches either ignore interactions or could test only a limited number of expected interactions; however, they can't detect all of them. In addition, argues Moskowitz et al. (2005), relative value of the utilities prevents from accumulating structured and reusable information as comparing data across the projects or even across attributes is not possible. The limitations listed above affect the usefulness of the existing approaches.

NPD methodologies have been deeply researched by the scholars, although almost exclusively for the industrial applications (Burchill and Fine, 1997; Calatone and Cooper, 1979; Cooper and Kleinschmidt, 1995, 1996; Ford and Sternman, 1998). Stewart-Knox and Mitchell (2003) concludes that not much work has been done for the food products and specifically for the mature categories. In addition, although a substantial research done in the general area of conjoint analysis (Rosenbaum, 1987; Hauser, and Rao, 2003; Toubia, Simester, Hauser, and Dahan, 2003; Krieger, Green and Wind, 2004; Orme, 2006), there is a research gap in the methodologies to discover any and all interactions in conjoint analysis.

There is also a need to determine the ways to create structured and reusable information of consumer preferences to product features and messages for new product development. Stewart-Knox and Mitchell (2003) argues that this low rate of innovation in the food industry, coupled with the high failure rate of food products following market launch implies that the methodology for new food product development urgently needs improvement.

The dissertation examines the existing and emerging methodologies in consumer-driven NPD for mature product categories (Studies I–III); studies an approach for detecting and estimating any and all interactions between the elements of conjoint analysis in utilized in NPD, including implicit and explicit interactions along with the underlying special experimental designs (Studies I and II); and formulates propositions for food corporations about the ways to create structured and reusable information of consumer preferences to product features and messages for new product development (Studies II and III).

The aim and research tasks

The **aim** of the dissertation is to develop a conjoint analysis-based product development methodology to increase consumer involvement in building industry usable product knowledge.

To fulfill the aim of the thesis, the following research tasks are put forward:

Task 1: To identify development opportunities in consumer-driven experimentation approaches to new product development.

Task 2: To improve the theoretical approach to the consumer-driven conjoint analysis-based new product development.

Task 3: To empirically study the proposed methodologies on the example of new product development in mature food categories.

The originality of research and its practical merit

An original aspect of the dissertation arises from the contribution to the theory of conjoint analysis. Many researchers studied the effect of interactions between the elements of the conjoint analysis. Green (1973), Rosenbaum (1987), Aiken and West (1991), Carroll and Green (1995), Hauser and Rao (2003), Krieger, Green and Wind (2004) have proved the existence of the interactions. Existing methods either ignore interactions or merely test a small set of them on a possibility of interactions (Chrzan and Orme, 2000). Several methodologies have been developed for testing and quantifying of pre-selected interactions. However our knowledge is still limited about detecting the interactions. This dissertation studies the issue and analyses proposed models and a methodology for estimation of interactions (synergy and suppression) between the elements of conjoint analysis (Study I). The research is based on U.S. Patent Application Serial No. 11/032,834 (Moskowitz and Gofman, 2005). It advances the research to the level of detecting any and all such interactions. The dissertation's further input to the research of interactions focuses on implicit interactions (scenarios) which help to uncover the variations in consumer preferences under specific constraints (e.g., impact of brands on the performance of other elements).

The proposed method for interactions detection as well as pattern-based latent mind sets segmentation process are based on individual experimental designs in conjoint analysis. These approaches are possible due to the methodology recommended to be called *permuted isomorphic experimental designs.* The general idea of the approach was first introduced in Moskowitz (1994) and Moskowitz et al. (1995) to address the issue of results distortion due to the lack of variability in selection of a specific set of combinations of elements in fractional experimental designs. Until now, the method was not deeply researched and generalized thus making its implementation difficult. An original aspect of the current dissertation is in the research of the permuted isomorphic fractional designs, which continues the initial steps introduced in

U.S. Patent Application Serial No. 11/032,834 (Moskowitz and Gofman, 2005), as well as implementation into a software package.

The dissertation also analyses several empirical studies in mature food categories (cookies in Study I and III, orange beverage in Study I and ice cream in Study II) with in-depth analysis including segmentation, interactions and demographic clustering. It studies consumer preferences on both conceptual and sensory preferences levels. Based on this large-scale project with 322 respondents participating in the conjoint analyses and 100 respondents in the sensory category appraisal, the dissertation proposes steps towards creation of structured and reusable information of consumer preferences of product features and messages for new product development with the data relevant for the process identified.

Another area of the research and originality of this dissertation is related to the proposed procedures and links allowing for the systematizing of knowledge about consumer preferences. The research is partially based on U.S. Patent 6,662,215 B1 (Moskowitz and Gofman, 2002) addressing the problem indirectly identified in Wind and Mahajan, (2001), which suggests that unstructured experimentation does not allow the knowledge accumulated in separate projects to be aggregated, compared and used for future research and NPD. This problem is also acknowledged in Khurana and Rosenthal (1998), Trott (2008) and others. Moskowitz et al. (2005) argues that the lack of such procedures is detrimental to the current innovation process and the attained *ad hoc* knowledge cannot be aggregated and used for consequent development.

One more aspect of originality of the dissertation is related to the research in combinatorial innovation in mature food categories. The premise of the research has been built on the works of Schumpeter further developed by Usher (1954), continued by Hounshell (1984), and later on, by Weitzman (1998), Haagedoorn (1996), Varian (2003), Langlois (2004), Nooteboom (1999) and Fagerberg (2006). This research showed that innovation could originate from the combination of existing features. Beckley et al. (2007) suggests that an approach that allows aggregation and comparison of the accumulated knowledge from multiple studies would facilitate innovation by sheer volume of the input material with the consumer metrics attached. This in turn facilitates a vision of Weitzman (1998) who introduced the notion of 'recombinant growth', on a grander scale. The Study III analyzes a novel parsimonious approach to this phenomenon that could lead to a framework for practical approaches to NPD in mature food categories.

The practical relevance of the research is highlighted by the need of businesses, identified in Beckley et al. (2007), to have an easy to deploy, inexpensive, fast and structured approach to NPD in mature product categories. The proposed methodology in this dissertation is recommended to be named *Rule Developing Experimentation (RDE)*. Earle (1997) puts forward a criteria for a successful process in food related NPD: it needs to be more 'focused, quantitative, rapid and knowledge based'. RDE aims to satisfy these criteria. In addition, the formalized common framework simplifies applications development and dissemination of knowledge in corporations. As it is applicable to other business areas as well, it could replace multiple methodologies specific to narrow applications with a unified approach thus simplifying the training and cross-training of the personnel. It also facilitates knowledge accumulation and re-use in different areas due to the underlying statistical foundation (absolute values of the utilities) as shown in Moskowitz et al. (2005), and Beckley et al. (2007).

The contribution of individual authors

The following briefly describes the contribution of the dissertant relative to the other authors.

Study I was authored by the A. Gofman (under mentorship of Dr. Moskowitz). The dissertant also played a pivotal role in the data collection stage of the study. A US patent has been filed with the main finding described in the study. A. Gofman performed all the work in the formulation, preparation and filing of the patent as well as all the communications with the legal representative and the United States Patent Office (USPO) and International patent authorities.

In Study II, the authors equally contributed to the text of the article. A. Gofman played a pivotal role in the design of the empirical part of the article, its data collection and analyses.

Study III has been equally authored by the dissertant and his co-author. A. Gofman was the presenting author of the main findings of this Study at The XVI ISPIM Annual Conference "The Role of Knowledge in Innovation Management" in Porto, Portugal, in 2005. This conference paper has been selected among the best papers of the event by the committee to be published in the International Journal of Technology Management (in an abbreviated form). The dissertant is the corresponding author for this paper.

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I. THE THEORETICAL AND EMPIRICAL BASIS FOR THE RESEARCH

I.1. Background of the research

I.1.1. Consumer-Driven New Product Development

In today's business environment, a continuous supply of novel products is essential to retaining competitive advantage. Jaeger et al. (2003), Buisson (1995), and Costa and Jongen (2006) state that NPD is often recommended as a suitable strategy to build competitive advantage and long-term financial success of companies in today's global food markets by approaching the development of new products more structurally. Lord (1999), Meulenberg and Viaene (1998), Trail and Grunert (1997), and van Trijp and Steenkamp (1998) demonstrate that product innovation helps maintain growth, spread the market risk, enhance the company's stock market value and increase competitiveness.

Calatone and Cooper (1979), Burchill and Fine (1997), Ford and Sternman (1998), and Stewart-Knox and Mitchell (2003) research progressively more sophisticated approaches to consumer-driven NPD, which emerged in the last decades, although a majority of them concentrate on industrial development rather than mature and saturated markets such as food products.

Buisson (1995) established that many food corporations utilize a *reactive approach* to NPD, in which companies try to market what was developed through marketing efforts rather than developing what consumers wanted in the first place. On the other hand, argues Urban and Hauser (1993), continuous collection and aggregation of the consumer-related data along with taking consumer needs as the starting point of product innovation efforts, makes it the quintessential example of a *proactive approach* to NPD.

User-driven innovation was first described by von Hippel (1976, 1978, 1988) who documented a number of cases where customers modified or adapted existing products according to their own needs before the industry did. Grunert et al. (2008) argues that today the term has an extended meaning and is applicable to all forms of consumer involvement in the innovation process. A number of related concepts exist in the literature, including *early customer integration* (Gassmann and Wecht, 2005), *participatory design* (Mayhew, 1999), and *user-centered development* (Ketola and Ahonen, 2005). Grunert et al. (2008) further suggests a variation of the term – *user-oriented innovation* which is defined as a process towards the development of a new product or service in which an integrated analysis and understanding of the users' wants, needs and preference formation play a key role. Costa and Jongen (2006), and Grunert and Valli (2001) demonstrate that users can be both direct customers and end users.

Consumer-led NPD was introduced in Urban and Hauser (1993), Urban et al. (1997), and further developed in van Trijp and Steenkamp (1998), and Vriens et al. (1998) along with others as a market-oriented innovation process that involves consumers' current and future needs and its determinants in the development of new products with true added value. Urban and Hauser (1993) identifies the key stages in the formulation of the consumer-led NPD concept follow closely a market-oriented approach: need identification, idea development to address the need, product development to substantiate the idea and the product's market introduction to communicate the fulfillment of a need (Figure 2). An effective ability to translate subjective needs (e.g. healthy or convenient) into objective product specifications is essential for the realization of the satisfaction of consumer wishes through the development of a new product. Concurrently, marketing strategies communicating the existence of a new or improved product, which satisfies consumer needs in a distinctive and superior way, must be initiated. Dahan and Hauser (2002), Grunert et al. (1996), Urban and Hauser (1993), van Trijp and Steenkamp (1998), and Wind and Mahajan (1997) prove that such a consumer-led approach to product development can greatly increase the likelihood of success of innovation processes.

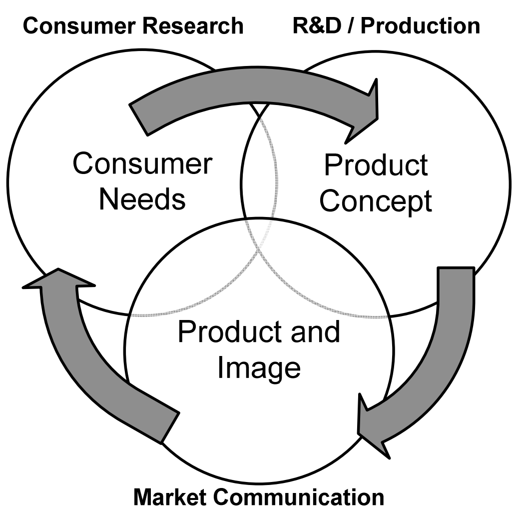


Figure 2. The Consumer-led NPD (Source: adapted from Urban and Hauser, 1993).

Fuller (1994), van Trijp and Steenkamp (1998), Stewart-Knox and Mitchell (2003) point to a somewhat sequential (rather than concurrent, overlapping or iterative) nature of consumer-led NPD as a conceptual weakness and a considerable obstacle to its application in the food industry. Wheelright and Clark (1992) proposes the *funnel* approach an improvement to consumer-led NPD. Cusumano and Selby (1995) addresses the shortcoming though the *spiral* approach. Both these approaches start with a broad range of ideas from several sources that are later winnowed to a few high-potential concepts, some of which will, in turn, be ultimately developed and launched.

Lord (1999), Moskowitz et al. (2005), and Beckley (2007) develop the consumer-driven approaches further, although there is a gap in the research of its theoretical foundations. In addition, there is a lack of methodological guidelines for its practical implementation.

A critical step in new product development is selecting from multiple possible product concepts the ones that the firm will introduce to the market-place. The two main approaches to the concept selection and choosing a design prior to detailed engineering and prototyping are the *method of controlled convergence* introduced in Pugh (1996) and *concept engineering* described in Burchill (1992). In contrast, Srinivasan, Lovejoy and Beach (1997) demonstrates that, depending on the cost of developing each concept into a customer-ready prototype, it would be optimal to carry *multiple product concepts* into the prototyping and testing phase, and to select the best of those designs later in the process, as depicted in Figure 3.

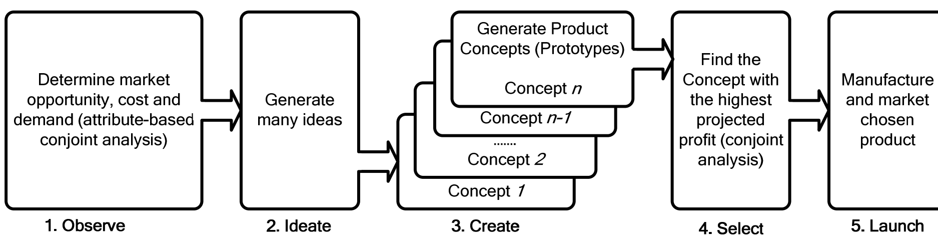


Figure 3. NPD Process consisting of five stages. Stages 1, 3 and 4 could utilize conjoint analysis. Source: Dahan and Srinivasan (2000) (author's rendering).

Dahan and Mendelson (1998) utilizes *extreme value theory* to determine the optimal number *n* of parallel prototypes and weigh the parallel testing against an iterative one. The paper argues that the optimal number of prototypes increases in situations when time to market is short and the cost of prototyping decreases. Stevens and Burley (1997), van Kleef, van Trijp and Luning (2005) and Wansink (2005) also point out the need to work with many prototypes to develop a successful product. This idea is further developed in Iansiti (1995) which identifies the advantages of this approach in added flexibility to respond to market and technological shifts along with an added benefit of shortening the total product development time in case of such shifts. The approach in general, argues Tawn (1988), is an improvement compared to than empirical curve-fitting and guesswork, although it does not resolve all the problems.

The *Voice of the Customer (VOC),* analyzed in Griffin and Hauser (1993), and Adams (2004), is a proactive and constantly innovative process used to capture the requirements/feedback from the customer (internal or external) to provide the customers with the best in class service/product quality. Carson et al. (2001) analyses VOC, which aims to detect the stated and unstated needs or requirements of the customer and can be captured in a variety of ways: direct discussion or interviews, surveys, focus groups, customer specifications, observation, warranty data, field reports, complaint logs.

Zaltman and Coulter (1995) demonstrate the application to identify the quality attributes needed for a supplied component or material to incorporate in the process or product. At the same time, argues Leonard (2002), VOC is limited to selection from the option known to consumers. When customers are asked to make new product recommendations or elaborate on topics they have limited or no knowledge, they tend to run into at least two kinds of blocks. The first is the human tendency to fixate on the way products or services are normally used, making people unable to imagine alternative functions. The second is that people may not be able to conceive of a solution because they might have contradictory needs.

Flores et al. (2003) points out that in previous years most of the attention in consumer research was focused on assessing products and concepts that were 'complete', 'polished', and ready to go. More recently, argues Reid and de Brentani (2004), attention has shifted from this late stage of development to a much earlier stage, where the options for development are open ('fuzzy front end'). Dahan and Mendelson (2001) suggests that the 'fuzzy innovation stage' is often ignored by consumer researchers in favor of the more defined, later stages of development where there are metrics, standard procedures, and recognized analytical approaches. As a result, argues Toubia (2004), the important first stage of product development is poorly executed, leaving the product not optimized, to survive the competition.

The idea generation and testing methods that comprise the fuzzy front end of NPD provide information to designers about the customer utility, technical feasibility, and cost of a new product. Allocating resources at this early stage poses a challenge considering the inherent uncertainty. In particular, uncertainty arises from imperfect information about customers and markets, undiscovered or untested product designs and technologies, and the challenges in executing and delivering an ideal design. Concept tests help resolve this uncertainty and encompass most methods used to measure the performance of new products and processes along those dimensions affecting profitability. Methods such as *VOC*, *contextual inquiry* (Raven and Flanders, 1996), *lead user analysis* (von Hippel, 2005), *conjoint analysis*, *Kano methods* (Shen, Tan and Xie, 2000), and *Pugh concept selection* (Dahan and Hauser 2001) clarify and focus the fuzzy front end of NPD. For example, Raven and Flanders (1996) shows that contextual inquiry and VOC methods help identify key product attributes. Green and Srinivasan (1990) points that conjoint analysis quantifies the importance of each attribute and the degree of price sensitivity, providing designers with the information needed to optimize attribute-level trade-offs for specific market segments.

This area, which got the attention of von Hippel (2005), has provided a range of examples of how certain users (lead users or less professionalized communities) can take on a role as designers to interact with product developers in companies. Research described in Grunert et al. (2008) shows that lead users are users whose present needs will become widespread in a market months or years ahead. Since lead users are familiar with conditions that lie in the future for most others, they can serve as a need-forecasting laboratory for market research.

Customer-ready prototypes, researched in Srinivasan et al. (1997), reveal technical problems and opportunities that might have been overlooked in the design's conceptual phase. *Product archeology* (Ulrich and Pearson 1998) and *design for manufacturability* (Boothroyd and Dewhurst 1994) help to identify potential cost savings through product simplification and process improvement, although they have limited applicability.

One process that increasingly gains acceptance is a *systematic recombination* of R&D-meaningful features, that could be enhanced by including the consumer preferences (Varian, 2003; Rabino et al., 2007). The latter implies that the combinations are directed, rather than being random (Varian, Farrell and Shapiro, 2004). Moskowitz et al. (2005) argues that this *combinatorial innovation* is especially applicable to food product NPD and could jump-start the innovation process even in mature categories.

Stewart-Knox and Mitchell (2003) points that models of the processes for the food industry should emphasize involving the consumer from the start of the process and consistently advocate the integration of technology and marketing efforts. One such model is the *House of Quality approach*, which is the first of four phases within *Quality Function Deployment (QFD)* (Costa, Dekker, and Jongen, 2001). Originally developed for improving automotive industry in Japan (Akao, 2004), QFD has recently been applied to food by van Trijp and Steenkamp (1998).

According to Akao (2004), Costa et al. (2001) and Garcia et al. (2007), QFD is a planning process for the design of new products that provides a systematic method for translating 'customer requirements' into design and process parameters – 'company requirements' analyzed in King (1992). In doing so, concludes Holmen and Kristensen (1998), QFD helps companies to reduce two types of risks: first, the non-correspondence between product specifications and the needs and wants of a predetermined target group of customers; and second, the non-correspondence between the final and the original product specifications. QFD is based on the belief that products should be designed to reflect customers' demands and needs. Therefore, the project requires top management commitment and organizational support, clear definition of project objectives and the creation of a cross-functional team including members from all functional areas involved in NPD and market introduction and consumer product testing (Costa et al., 2001; Hauser and Clausing, 1988).

The literature on the application of QFD in the food industry is limited (Costa, Dekker and Jongen, 2001 provides a brief review). While QFD is regarded as a suitable and promising method to increase the innovative performance of the food industry, Dekker and Linnemann (1998), and Costa et al.

(2001) indicate that QFD still needs significant development and understanding before the method can be extensively applied in new food product development.

Interactions between attributes can play a decisive role in achieving consumer satisfaction. Garcia et al. (2007) argues that raw materials have a natural predisposition for variation that does not fit well with the somewhat inflexible character of QFD charts described in Dekker and Linnemann (1998). Many food ingredients show interactions and some HOWs could affect more than some WHATs. These interactions and the large list of customer demands are often seen as the major bottlenecks of using QFD in new food product development (Ibid).

According to Nijssen and Frambach (2000), one of the major and most obvious gaps in consumer-driven food product development is the lack of clear and concrete guidelines for its effective implementation in everyday company practices. This deficiency is felt mostly at the early phases of the development process – opportunity identification and opportunity definition – which, as shown in Nijssen and Lieshout (1995), are simultaneously the less structured and the more determinant for the success of new products. Anderson-Connell, Ulrich, and Brannon (2002) describes companies trying to use traditional qualitative methods to improve the process such as *focus groups*. Prescott et al. (2002) researches *Food Choice Questionnaire (FCQ*), which assess the relative importance of factors thought to be important motives in food choice: Health, Mood, Convenience, and Sensory Appeal. This in turn, argues Deliza (2003), could be modeled using *conjoint analysis* in addition to traditional taste tests.

A methodology that gained some popularity in recent years is *preference mapping techniques*. According to Greenhoff and MacFie (1994), while the methodology can be used to address a wide range of problems, it is particularly suited to aid new product development. In such applications, the methodology can assist in identifying product opportunities in the market. Although the approach has the ability to combine sensory profiles and acceptability data to identify the sensory attributes driving consumer acceptance, its applications are limited. Murray and Delahunty (2000) show the advantages and disadvantages of the approach on the example of Cheddar cheese.

Cooper and Kleinschmidt (1994), Grunert et al. (1996), Saguy and Moskowitz (1999), Urban and Hauser (1993), and Beckley et al. (2007) establish that understanding consumer needs and reacting effectively to them is believed by many researchers to be one of the most important correlates of product development success. However, there are some questions remain regarding the value of consumer focus in NPD. It has been stated that consumer-driven development activities, by following closely consumer needs, encourage incremental innovation in detriment to the development of truly new products. Atuahene-Gima (1995), Ortt and Schoormans (1993), van Trijp and Schifferstein (1995), Wind and Mahajan (1997) point to the main argument sustaining this view is that consumers cannot be expected to provide needs about products or technologies which are yet unknown to them. In line with this argument, several methodologies, such as *consumer-idealized design* (Ciccantelli and Magidson, 1993), *problem* and *lead-users design* (Ortt and Schoormans, 1993; von Hippel, 1986), *beta-testing* (Kaulio, 1998) and *information-acceleration* (approach which places consumers in future technological scenarios) (Urban and Hauser, 1993), have been developed to overcome this obstacle.

The lack of systematic accumulation of knowledge obtained during the new product launches (both successful and failed) has a negative impact on the effectiveness of NPD. On the other hand, Deshpandé and Zaltman (1982), Inkpen and Dinur (1998), Li and Calatone (1998), Davenport and Klahr (1998), Arnett, Menon and Wilcox (2000), De Luca and Atuahene-Gima (2007) show that the integration of this information into knowledge management assets of corporations continuously from the R&D step all the way to the launch could substantially improve the chances for success. Sherman, Berkowitz and Souder (2005) demonstrates that the combined effect of R&D and marketing integration and knowledge management in the form of recording, retrieving, and reviewing information from past projects result in the amplification effects on product prototype development proficiency, product launch proficiency, technological core competency fit, and design change frequency.

Consumer-driven NPD is an increasingly important methodology for food industry. There are emerging opportunities to research and develop it further that will be discussed in the following sections.

1.1.2. Conjoint Analysis Approaches and Consumer Segmentation

Krieger, Green and Wind (2004) states that conjoint analysis has become increasingly prevalent as a major approach to studying consumer preferences. Partially it could be explained, argues Arora and Huber (2001), by the fact that the experimentation afforded by conjoint analysis enables researchers to model choices in an explicit competitive context to realistically emulate market decisions. In addition, points out Atkinson and Donev (1992), conjoint analysis represents one of the major tools in concept development based on experimental design increasingly used for NPD (Brigham Young University, 2007; Orme, 2006; Jedidi and Zhang, 2002). Conjoint analysis first introduced in Luce and Tukey (1964) was founded on the idea of functional measurement summarized in Anderson (1977), who averred that the researcher could learn a lot by studying combinations of stimuli and applying a decompositional rule, such as analysis of variance or regression analysis to the mixture.

In conjoint analysis, products are defined on a limited number of relevant attributes or characteristics (categories of features or emotional attributes of new products) each with a limited number of levels (elements). These products, called profiles or concepts, are evaluated by respondents, who have to rate them, as used in the present thesis, rank them or choose their most preferred ones from smaller sets of choices (in other conjoint analysis methodologies).

As classified in Louviere (1988), the conjoint analysis methodology is a decompositional approach to analyze consumer preferences. Respondents provide overall scores to a concept (product profile) and the analysis imputes what the preference contributions are for each separate attribute and level. The overall utility of a product profile is constructed by adding the attributes' preferences (impacts or utilities) resulting in a *compensatory preference model*, where "low" scores on a certain attribute can be compensated by a "high" score on another attribute. As demonstrated by Vriens (1995), *non-compensatory preference models* that assume that certain attributes must have a minimum or maximum level before a profile is considered attractive could be utilized as well.

In the marketing world, conjoint analysis is best known for being a research technique by which one can investigate combinations of features to identify which combination is best. Developed by Paul Green and his colleagues at Wharton School of the University of Pennsylvania (Green and Srinivasan, 1981), conjoint analysis is now a technique widely used in high profile products to design products and services in different categories (Green and Rao 1971; Johnson 1984; Rosenbaum, 1987; Wittink and Cattin, 1989). Reviewing the history of conjoint analysis, Krieger et al. (2004) concludes that since the early 80s, it is the industry's most widely applied marketing research tool for measuring buyers' multi-attribute utility functions.

In the process of evaluating systematically created combinations, the elements of the concept constitute the independent variables, and the attribute ratings are the dependent variable. Hair et. al. (1995) points that the concept elements must be independent of each other or else the criteria to create an additive model by regression would be violated. To be useful for NPD, these elements have to be meaningful within a concept, and ideally realizable in an actual product. At the very practical level the concept must be readable.

Full-profile conjoint analysis presents the test concepts containing at least one element from each category. Krieger et al. (2004) concludes that it is the methodology of choice for purchases where a person typically buys a single product. Full-profile conjoint analysis has the ability to show full product designs, which replicates the way products are actually purchased and it can generate individual models per respondent. This information allows the marketer to identify a "most preferred" product for each respondent that more closely reflects real-world purchase behavior. Green and Srinivasan (1981) points to a key drawback of full-profile – the limit of about six attributes with no more than 5–9 levels each. This limitation does not allow highly complex products to be fully described. The existing full profile approaches utilize the same underlying experimental design thus reducing the variations of the concepts and elements combination making it difficult to detect interactions between the elements. In addition, Krieger et al., (2004) demonstrates that full-profile conjoint analysis assumes that all attributes are independent of one another thus generating the absolute utilities values making it impossible to compare utilities across the attributes. We will analyze these issues in more details in the following sections and in Study I.

In *partial-profile* conjoint analysis, continues Krieger et al. (2004), some features are explicit and other features are assumed to be constant. The number of the elements on the screen could vary from two to many. Kuhfeld, Tobias, and Garrant (1994) argues that it is highly suited for computer interviewing and thus became very popular. The existing approaches to partial-profile conjoint analysis usually utilize a single (sometimes randomized) experimental design thus reducing the variations of the concepts and elements combination making it difficult to detect interactions between the elements.

Discrete choice conjoint analysis is most frequently utilized for products where consumers purchase multiple products distributed over many brands over the course of a year in proportion to the relative desirability of those products. According to Green and Srinivasan (1978) and Krieger et al. (2004), its advantages include a tolerance towards perceptional incoherency of the concepts; flexibility to direct combinations of the elements with selected constrains (e.g., showing certain features with one brand and a different set of features only with another brand); some ability to measure interactions between two attributes, such as between price and brand. At the same time, discrete choice is less applicable to NPD than other methodologies. Moskowitz et al. (2005) demonstrates that it can only be analyzed at the aggregate level thus eliminating the ability to segment consumers in a tractable way based on the patterns of their individual utilities. Discrete choice conjoint analysis measure is not typically able to generate accurate market share due to the inability to make respondent level adjustments for volume purchasing, unequal awareness and/or distribution.

According to Green and Srinivasan (1990a), early applications of conjoint analysis used relatively few concept elements. These elements tended to be the more rational features found in products, since these early studies focused on the design of products using conjoint analysis. With the acceptance of the methodology in general, the need arose to increase the number of the elements in a project to 100–300 elements.

One traditional way for coping with many elements is to have each respondent select the concept elements that would be most appropriate to him, and to discard the rest. This procedure requires that the respondent explicate importance before participating in the *hybrid conjoint analysis*. This general strategy, called *Adaptive Conjoint Analysis (ACA)* (Johnson, 1987), works only with relevant concept elements and respondents willing to explicate their preferences ahead of time, or at least explicate directly relevant elements. Toubia et al. (2003) argues that adaptive conjoint analysis works best when all of the elements are similar in terms of quality (e.g., simple statements about product functionality that can be judged alone, and accepted or discarded as being relevant or irrelevant).

Krieger et al. (2004) analyses three problems with such adaptive approaches that make adaptive conjoint analysis a less than desirable approach to deal with a large number of concept elements: substantial up-front efforts for respondents;

forcing respondents to make difficult rational decisions on unnatural for most individual element level rather than a combination of the features; and inability to create individual models.

Until recently, most applications of conjoint analysis either presented the same set of concepts to all respondents, blocked them across sets of respondents, chose randomly, or adapted them based on responses from prior respondents. Adaptive question design for individual respondents was first considered by Toubia et al. (2003, 2004) in metric paired-comparison settings. This new approach, named the polyhedral method, works by iteratively constraining the polyhedron of feasible sub-utility (part-worth) values. Since the problem is computationally hard, many approximations, such as *Q-Eval* proposed in Iyengar et al. (2001), are employed. Toubia et al. (2003) and Toubia (2004) extend this technique to metric paired-comparison queries in. At the same time, the polyhedral method solves only one of the three intrinsic problems for adaptive conjoint analysis, the lack of individual models.

There are other approaches that use estimation procedures to fill in missing elements, but these procedures are cumbersome and are removed from the utility data (Green and Krieger, 1996; Hauser and Rao, 2003). One of the methods researched by some statisticians lately is Bayesian model. Although the method provides some improvements to conjoint analysis, it is highly computationally intensive (partially due to the utilization of Markov chain Monte Carlo sampler) and requires high level of statistical proficiency as shown in Marshall and Bradlow (2002). Rossi, Allenby, and McCulloch (2006) point that the process is lengthy and expensive which severely restrict its practical usability by corporations.

Conjoint analysis provides three specific benefits in the early stage process that can identify weak signals:

1. By forcing the researcher or ideation expert to edit the elements, one forces better thinking. According to Johnson (1984), Green and Srinivasan (1978, 1981, 1990a, 1990b), the concept elements have to be simple, stand-alone ideas, phrased in the active case. Kessels, Goos and Vandebroek (2008) summarizes that just emerged from ideation, the idea is frequently poorly expressed. Moskowitz et al. (2005) concludes that the elements themselves mature from simple notions to better-expressed statements. Flores et al. (2003) suggests that the exercise itself is as valuable as the ultimate discovery of weak signals.
2. The performance of ideas is judged against different backgrounds, encouraging 'survival of the fittest'. Conjoint analysis uses experimentally constructed concepts comprising several different ideas. Kantowitz, Roediger and Elmes (2008) argues that to the degree that a concept element performs well in multiple backgrounds, one can be sure that the idea is good. According to Wind and Mahajan (2001), this rigorous test speeds up the development process because it creates an objective method to identify good ideas.
3. Conjoint analysis leads to segmentation, which may reveal the great promise of an idea, otherwise masked among the averaged data. Segmen-

tation is key to achieving increasing acceptance because consumers do not share the same preferences. As pointed by Green and Krieger (1991), Riquelme (2001), Zaltman (2003), Neal (2003), Rabino (2007), and Beckley et al. (2007), what appeals to one consumer may not appeal to another.

Many scholars, such as Crow, Davis and Maxfield (1960) and Bretscher (1995) agree that one of the most frequently used regression models in conjoint analysis is the *Ordinary Least Squares* OLS regression. Gelman and Hill (2006) argues that it offers a simple, yet robust method of deriving alternative forms of respondent utilities (part-worth, vector, or ideal point models).

According to Bretscher (1995) and Wolberg (2005), the advantages of OLS are due to its simplicity of analysis and the intuitive meaning as well as the capability to scale respondent choices using rating scales, rather than rankings. Reviewing many other methods, Harrell (2008) concludes that the ability to implement designs having larger numbers of attributes and levels (through fractional factorial designs described below) has made this methodology the *de facto* standard for conjoint analysis .

Rao et al. (1999) formulates the objective of OLS in conjoint analysis as to produce a set of additive part-worth utilities (vector or ideal point utilities may also be estimated) that identify each respondent's preference for each level of a set of product attributes. In application, the OLS model uses a dummy matrix of independent variables described in Encyclopedia of Statistical Sciences (1985) and further researched in Wolberg (2005). Each independent variable indicates the presence or absence of a particular attribute level. The dependent variable is the respondent's evaluation of one of the profiles described by the independent variables. This model is expressed:

$$U(x) = const + \sum_{i=1}^{n} b_i x_i \tag{1}$$

where b_i are called *partial regression coefficient*s (part-worths or impacts) of the independent variables x. They measure the variation in the value of $U(x)$ that is due to a variation by one unit of the independent variables (Green and Devita, 1975). In the context of a conjoint analysis project with a purchase intent anchored question, the coefficients could be interpreted as a conditional probability of consumers being interested in buying this product.

The most utilized way of conducting conjoint analysis research now is over the Web. Initially, due to the low penetration of the Internet, there were concerns about representativeness of the Internet samples and the general validity of the Web research as addressed by Mizuno (1997) and Melles, Laumann and Holling (2000). By early 2000s, these concerns were partially answered due to the proliferation of Internet and improved methodologies analyzed in Dahan and Srinivasan (2000), Lynn et al. (2002), Kraemer and Dedrick (2002), Tourangeau (2004), Constantinides and Geurts (2005).

Segmentation refers to the division of respondents by one or another set of criteria such that respondents in one segment are more similar on a set of criterion attributes. Neal (2003) defines market segmentation as the selection of groups of people who will be most receptive to a product. Wind et al. (1989), Neal (2003), Beckley et al. (2007) argue that segmentation of consumers into groups with similar preferences may provide an additional opportunity for product developers to create new and innovative products. As demonstrated by Monahan (2003), demographics could not explain the distinctly non-demographic difference between people.

Well-defined segments are easier to target with specific products and market strategies. Gathering more relevant and predictive lifestyle and demographic information on the potential consumer allows the company to develop greater depth of knowledge about the targeted market and consumer.

Moskowitz et al. (2005) and Beckley et al. (2007) point that in general, segmentation can be accomplished in two different ways – *a priori* segmentation and *a posteriori/post hoc* or latent-based segmentation.

In *a priori segmentation*, the segments are developed by certain theory-derived assumption about the preferences of the respondent. Neal (2003) points that a large share of segmentation is done using exogenous variables such as geo-demographic characteristics, where the assumption is that people from different geo-demographic 'breaks' may exhibit different utilities.

A posteriori/post hoc or latent-based segmentation emerges from the individual utilities in conjoint analysis or characteristics such as responses to a series of attitudinal questions, as suggested in Green and Krieger (1991). The results, further develops Krieger et al. (2004), generate an interesting and often profitable way to divide a group of respondents. The utility values from conjoint analysis can and have been used as bases for segmentation. Pangborn (1970) analyzes a method in sensory preference segmentation first introduced in food research, but not necessary for individual respondents, and later adapted for concept studies. Another method uses the pattern of utilities themselves, developing a distance measure between pairs of respondents based upon a distance metric such as (*1-R,* where *R* is Pearson correlation coefficient between two sets of utilities). Green and Krieger (1991); Vriens (1995); Neal (2003); Moskowitz et al. (2005); Moskowitz, Itty and Manchaiah (2005), Beckley et al. (2007); Lee et al. (2007) discuss the different segmentation methods.

1.2. Refined Methodological Basis

1.2.1. Exploring New Methods in Experimental Design: Isomorphic Permuted Experimental Designs

Experimental design is a foundation of conjoint analysis, as well as several other experimentation-based approaches. Atkinson and Bailey (2001) define experimental design as a statistical plan that lays out the combinations of the concept elements. Despite of substantial research that has been done in the field and presented in Raghavarao (1971), John and Mitchell (1977), Cheng (1978), Bechhofer and Tamhane (1981), Cattin and Wittink (1982), Cheng and Bailey (1991), Atkinson and Donev (1992), Cochran and Cox (1992), Bagchi and Cheng (1993), Carroll and Green (1995), Chaloner and Verdinelli (1995), Atkinson and Haines (1996), Sniderman and Grob (1996), Quinn and Keough (2002), the field is still active and presents an opportunity for research.

In an experimental design, states Campbell and Stanley (1966), the combinations of elements, i.e., the test concepts, are designed so that the elements within the concept appear independently of each other in a statistical sense. Box et al. (2005) presents a variety of experimental designs varying in the number of factors (applied to attributes in conjoint analysis), and the number of levels (matched to the elements in conjoint analysis).

According to Box et al. (2005), a *factorial experiment* (or a *full factorial design*) is an experiment whose design consists of two or more factors, each with discrete possible values or levels, and whose experimental units take on all possible combinations of these levels across all such factors. A 2^k factorial experiment can be recursively designed from a 2^{k-1} factorial experiment by replicating the 2^{k-1} experiment, assigning the first replicate to the first (or low) level of the new factor, and the second replicate to the second (or high) level. This framework can be generalized to designing, for example, three replicates for three level factors, etc. Due to the large number of experimental units, for the vast majority of factorial experiments, each factor has only two levels. For example, in case of two factors with each taking two levels, a factorial experiment would yield four treatment combinations.

In situations when the number of combinations in a full factorial design is too high to be logistically feasible, *fractional factorial designs* are utilized (used in the dissertation). In these designs, some of the possible combinations are absent. Box et al. (2005) analyses fractional factorial designs consisting of a carefully chosen subset (fraction) of the experimental runs of a full factorial design. Beres and Hawkins (2001) points that the subset is chosen to exploit the *sparsity-of-effects* principle to expose information about the most important features of the problem studied, while using a fraction of the effort of a full factorial design in terms of experimental runs and resources. Fractional designs could be described using the notation l^{k-p}, where l is the number of levels of each factor, k is the number of factors, and p is the size of the fraction of the full factorial. For example, a 2^{5-2} design is 1/4 of a two level, five factor factorial design. Instead of the 32 runs that would be required for the full 2^5 factorial design, this experiment requires only eight runs.

Moskowitz et al. (2005) points that the concept could be created according to an experimental design in one of two approaches. In a *complete concept approach* (used in full profile conjoint analysis for example), every combination of the elements must have all the categories present (at least one of the elements from each attribute). An example of such a design is shown in Table 1 (right panel), where numbers represent elements (levels) of the attributes (factors).

Montgomery (2001) argues that for such designs it is impossible to estimate the absolute utility value of an element. Rather, the utility values are estimated relative to a reference value. The *reference element* is one of the concept elements, usually subjectively selected. With complete concepts approach, one cannot compare the utilities of elements across different categories of concept elements. Rather, one can only compare the utilities of elements within the same attribute.

Table 1. Comparison of examples of two types of designs. Numbers represent levels of the variables (factors). (Source: based on Moskowitz et al., 2005).

N	**Incomplete Concepts (with zero conditions)**			**Complete Concepts**		
	Var^1	**Var**^{2}	**Var**^{3}	**Var**^{1}	**Var**^{2}	**Var**^{3}
1	ABSENT	3	1	1	1	1
2	4	ABSENT	3	1	2	2
3	1	4	ABSENT	1	3	3
4	1	1	4	1	4	4
5	2	1	1	2	1	2
6	1	2	1	2	2	3
7	ABSENT	1	2	2	3	4
8	3	ABSENT	1	2	4	1
9	2	3	ABSENT	3	1	3
10	2	2	3	3	2	4
11	4	2	2	3	3	1
12	2	4	2	3	4	2
13	ABSENT	2	4	4	1	4
14	1	ABSENT	2	4	2	1
15	4	1	ABSENT	4	3	2
16	4	4	1	4	4	3
17	3	4	4			
18	4	3	4			
19	ABSENT	4	3			
20	2	ABSENT	4			
21	3	2	ABSENT			
22	3	3	2			
23	1	3	3			
24	3	1	3			

Krieger et al. (2004) and Moskowitz et al. (2005) describe another type of designs, sometimes called *incomplete concepts* (or with concepts having *zero conditions*). By arraying the combinations of concept elements in a specified experimental design with true zero's, i.e., with some combinations entirely missing an attribute, the researcher can estimate the absolute values of the utilities (see Table 1, left panel). As these designs are longer to be balanced, they require more concepts. In Table 1, the complete concepts design needs 16 concepts while a corresponding incomplete concepts one needs 24. Lee et al. (2007) argues that this drawback is more than compensated in a majority of cases by the ability of these designs to generate absolute values allowing for comparison between the categories and under specific situations, across the projects.

The research of the previous section singled out OLS as one of the most used regression methods for conjoint analysis. Gelman and Hill (2006) analyses one very useful form of OLS utilized in the current dissertation which is known as *dummy variable* because the elements take on one of two values: '0', if the element is absent from the concept, and '1' if the element is present in the concept. Appendix A (Table A-1) contains an example of an experimental design recorded into a dummy variable matrix to facilitate regression analysis.

The conjoint analysis approach used in the dissertation relies on an experimental design that presents incomplete concepts to respondents (with occasionally missing elements from some concepts).

This strategy has four key advantages over the conventional complete concepts (full profile) method summarized below:

- discovery and estimations of interactions between pairs of elements, and thus discovery of new major opportunities
- meaningful absolute values of utilities and therefore study-to-study databasing
- true zero and thus true baseline
- easier fielding due to shorter concepts.

A particular fractional experimental design is presented in the 'Original Design' section of Table 2 (left part) showing the Plackett Burman 5-Level screening design (Encyclopedia of Statistical Sciences, 1985).

This experimental design in general enables the researcher to investigate up to 5 attributes in a concept, and up to 4 elements per attribute. In the incomplete concepts approach, the fifth element is reserved for "null" or "no element present" (depicted as '0') situations. By allowing for a true null "zero condition", the researcher can use the regression analysis to better estimate the contribution of every element to respondent reactions (Moskowitz et al*.,* 2005). The design can deal with many elements using relatively few combinations, and still allow for a valid regression model at the individual respondent level.

In the right section of Table 2 ('Generalized for Permutation'), x_j^i is a permuted design selection rule, where *i* is a permuted attribute number and *j* is permuted element number.

Fractional designs introduce some level of bias due to the selection of a specific set of combinations required by the design (Moskowitz et al., 1995). Moskowitz (1994) suggests an approach that permutes the structure of the underlying fractional design to make multiple different sets of combinations. Initial steps towards formalization of the process has been described in

Moskowitz and Gofman (2005) and further developed by the dissertant in the current thesis. The resulting approach is suggested to be called *Isomorphic Permuted Experimental Designs (IPED)*.

The aim of the permutation of the fractional experimental design is to create *isomorphic designs* that are statistically equivalent to each other while combining different sets of the elements in different combinations. The approach aims to reduce a chance that the data will be affected by one or two unusually strong performing or poor performing combinations.

Table 2. An example of an experimental design for 25 concepts, based on the Plackett Burman screening design. (Source: Original Design – Encyclopedia of Statistical Sciences, 1985; Generalized for Permutation design – generalization proposed by the author based on Moskowitz and Gofman, 2005)

	Original Design					Generalized for Permutation				
N	Var^1	Var^2	Var^3	Var^4	Var^5	Var^1	Var^2	Var^3	Var^4	Var^5
1	4	1	3	1	1	x_4^1	x_1^2	x_3^3	x_1^4	x_1^5
2	0	4	1	3	1	x_0^1	x_4^2	x_1^3	x_3^4	x_1^5
3	3	0	4	1	3	x_3^1	x_0^2	x_4^3	x_1^4	x_3^5
4	3	3	0	4	1	x_3^1	x_3^2	x_0^3	x_4^4	x_1^5
5	2	3	3	0	4	x_2^1	x_3^2	x_3^3	x_0^4	x_4^5
6	3	2	3	3	0	x_3^1	x_2^2	x_3^3	x_3^4	x_0^5
7	4	3	2	3	3	x_4^1	x_3^2	x_2^3	x_3^4	x_3^5
8	1	4	3	2	3	x_1^1	x_4^2	x_3^3	x_2^4	x_3^5
9	2	1	4	3	2	x_2^1	x_1^2	x_4^3	x_3^4	x_2^5
10	2	2	1	4	3	x_2^1	x_2^2	x_1^3	x_4^4	x_3^5
11	0	2	2	1	4	x_0^1	x_2^2	x_2^3	x_1^4	x_4^5
12	2	0	2	2	1	x_2^1	x_0^2	x_2^3	x_2^4	x_1^5
13	4	2	0	2	2	x_4^1	x_2^2	x_0^3	x_2^4	x_2^5
14	3	4	2	0	2	x_3^1	x_4^2	x_2^3	x_0^4	x_2^5
15	0	3	4	2	0	x_0^1	x_3^2	x_4^3	x_2^4	x_0^5
16	0	0	3	4	2	x_0^1	x_0^2	x_3^3	x_4^4	x_2^5
17	1	0	0	3	4	x_1^1	x_0^2	x_0^3	x_3^4	x_4^5
18	0	1	0	0	3	x_0^1	x_1^2	x_0^3	x_0^4	x_3^5
19	4	0	1	0	0	x_4^1	x_0^2	x_1^3	x_0^4	x_0^5
20	2	4	0	1	0	x_2^1	x_4^2	x_0^3	x_1^4	x_0^5
21	1	2	4	0	1	x_1^1	x_2^2	x_4^3	x_0^4	x_1^5
22	1	1	2	4	0	x_1^1	x_1^2	x_2^3	x_4^4	x_0^5
23	3	1	1	2	4	x_3^1	x_1^2	x_1^3	x_2^4	x_4^5
24	1	3	1	1	2	x_1^1	x_3^2	x_1^3	x_1^4	x_2^5
25	4	4	4	4	4	x_4^1	x_4^2	x_4^3	x_4^4	x_4^5

Furthermore, by allowing each respondent to rate different sets of combinations, the researcher lays the groundwork for studying interactions among variables, which could not be studied before without creating the specific combinations wherein the interactions were thought to exist.

Although the general idea of permuted designs is known, there is no a formalized or generalized model / description of the approach. The dissertation studies this gap and proposes the following generalized mathematical model of the IPEDs.

Figure 4 shows Conceptual Model for the traditional approaches to experiential design in which an original experimental design (e.g., Plackett Burman screening design) is applied to a set of variables only once creating a single design for all respondents. Sometimes, this design is randomized (the same design with limited number of concepts, just the order of the concepts is randomized).

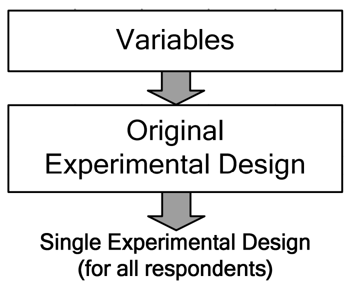


Figure 4. Conceptual model of a traditional experimental design applied to a set of variables to create a single design for all respondents. (Source: created by the author).

A drawback of this approach is that it tests the elements in a limited set of combinations thus preventing detection of all interactions. Moskowitz et al. (2005) also points to a bias introduced due to the limited and fixed number of concepts tested by the respondents. In such designs only a small fractions of higher order interactions (between three or more elements) are tested.

The proposed conceptual model of IPED (Figure 5) creates multiple permutations of the variables and levels (matched to attributes and elements in conjoint analysis) *before* the experimental design is individually applied thus creating distinct designs for each respondent with large total number of unique concepts. The experimental design is independent of any specific set of elements and attributes (as long as there is a match in the structure). If we randomize the sequence of the attributes and elements before applying the experimental design, we can theoretically create a large number of unique concepts comprising unique individual designs (up to statistical limits imposed by the specific design). This in turn creates a diverse contextual environment for concept testing producing as a result less biased results (Moskowitz et al., 2005). In addition, it creates a database of information which could be used for identifications of the interactions between the elements in the design as it evenly tests all pairwise and higher order interactions with a sufficient sample.

In an experimental design with attributes *(A_1, A_2, ..., A_n)*, an experimental unit c_i (line *i* of the design) could be described as shown in Figure 6. A randomized subset $R_k \subseteq (A_1, A_2, ..., A_n)$ is selected from the original set of attributes *A*. R_k contains attribute placeholders (*virtual attributes*).

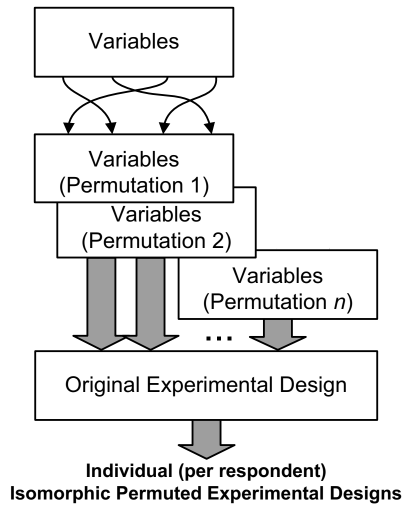
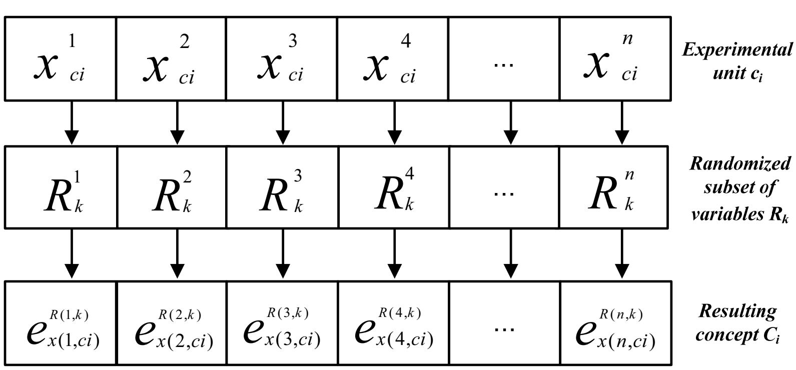


Figure 5. Conceptual model of proposed Isomorphic Permuted Experimental Designs (IPED). (Source: created by the author).



x^{l}_{ci} **is the experimental unit c_i for variable *l*.**

R^{n}_{k} **is an attribute placeholder *j* in randomization *k***

$e^{R(h,k)}_{x(h,ci)}$ **is an element in the concept C_i, where *R(h,k)* is the actual attribute assigned to the placeholder *h* during randomization *k***

$x(h,ci)$ **is the element number in the attribute *R(h,k)* corresponding to the experimental unit c_i**

Figure 6. Creation of isomorphic permuted experimental designs. (Source: created by the author).

For example, the first element of R_k (R_k^1) might contain attribute A_4 from the original set of attributes; R_k^2 might contain A_1, etc. In another randomization, the placeholders will contain different attributes. Then, the experimental units are applied to the randomized (virtual) set of attributes to create individual designs for respondents containing the elements $e_{x(h,ci)}^{R(h,k)}$, where $R(h,k)$ is the actual attribute assigned to the placeholder h during randomization k; $x(h,ci)$ is the element number in the attribute $R(h,k)$ corresponding to the experimental unit c_i.

Figure 7 shows examples of such application of an experimental unit to randomized sets of attributes. A single experimental unit is shown (from Table 2, line 1). In Set 1, the original order of the attributes (A, B, C, D, and E) is used thus creating the concept

$$C_i^1 = \{A_4|B_1|C_3|D_1|E_1\}, \tag{2}$$

where C_i^1 is concept i for set 1; X_j is element j of attribute X ($X \subseteq$ (A, B, C, D, E)). The same process is applied to the set of the attributes for the rest of the experimental units of the current design.

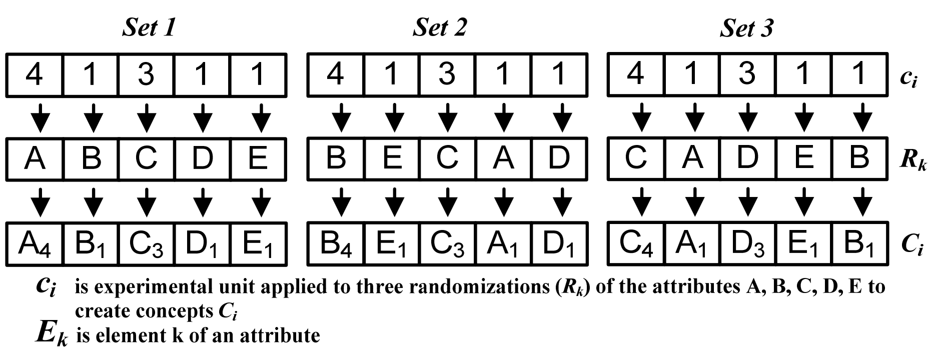


Figure 7. Examples of the of isomorphic permuted experimental designs. (Source: created by the author).

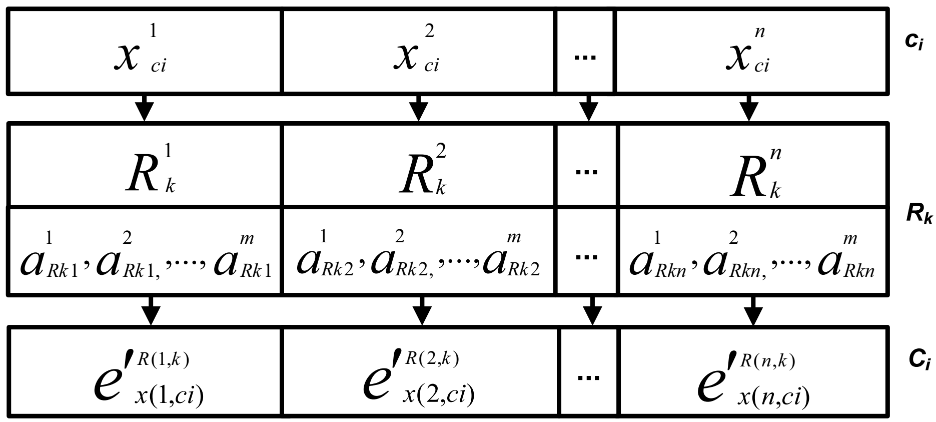
For Set 2, the order of the categories is different (B, E, C, A and D). The same experimental unit applied to the new randomization (virtual attributes) would produce another concept:

$$C_i^2 = \{B_4|E_1|C_3|A_1|D_1\}\,. \tag{3}$$

Note that the element numbers are the same as for C_i^1 although the attributes are different. For Set 3, the resulting concept is:

$$C_i^3 = \{C_4|A_1|D_3|E_1|B_1\}\,. \tag{4}$$

To make combinations of the elements more evenly distributed, thus enhancing the process further, the idea of the virtual attributes could be augmented with the notion of *virtual elements* (placeholder elements). For each randomization, in addition to randomizing the attributes order, the elements order in each attribute could be randomized as well, as shown in Figure 8.



C_i	**is an experimental unit**
x^{n}_{ci}	**is value of variable *n* in experimental unit c_i**
R_k	**an individually randomized array of attributes**
R^{j}_{k}	**is an attribute placeholder *j* in randomization *k***
a^{u}_{v}	**is an element *v* of the actual attribute *u* contained in the placeholder R^{j}_{k}**
$e'^{R(h,k)}_{x(h,ci)}$	**is an element in the concept C_i, where *R(h,k)* is the actual attribute assigned to the placeholder *h* during randomization *k***

Figure 8. Creation of augmented isomorphic permuted experimental designs that includes permutation of the elements and the attributes. (Source: created by the author).

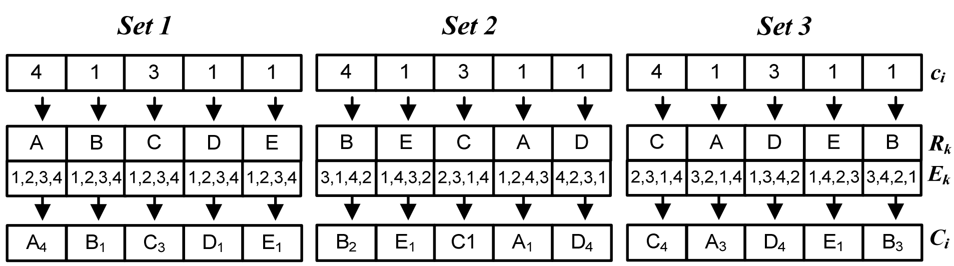
Figure 8 shows the case of the experimental design with the same number of the variables as the number of attributes. x^{l}_{ci} is the experimental unit c_i for variable *l*. With a set of attributes ($A_1, A_2, \dots, A_n$), the experimental units are applied to an individually randomized array of attributes $R_k \subseteq (A_1, A_2, \dots, A_n)$.

An attribute placeholder *j* (R^{j}_{k}) in the randomization *k* contains actual attribute while element placeholders a^{u}_{v} (element placeholder *v* of the virtual attribute *u* contained in the placeholder R^{j}_{k}) contain actual elements' numbers. $e'^{R(h,k)}_{x(h,ci)}$ is an element in the concept C_i, where *R(h,k)* is the actual attribute assigned to the placeholder *h* during randomization *k*; *x(h,ci)* is the actual element number in the attribute placeholder *R(h,k)* with elements placeholders $a^{h}_{R(h,k)}$ corresponding to the experimental unit c_i .

Figure 9 shows examples of the augmented IPED. It uses the same experimental unit as in the example above. In Set 1, the original order of the attributes (A, B, C, D, and E) as well as the original order of the elements are utilized thus creating the concept:

$$C_i^1 = \{A_4|B_1|C_3|D_1|E_1\}\,, \tag{5}$$

where C_i^1 is concept i for Set 1; X_j is element j of attribute X ($X \subseteq (\mathrm{A, B, C, D, E})$). The same process is applied to the set of the attributes for the rest of the experimental units of the current design.



c_i* is experimental unit applied to three randomizations (*R_k*) of the attributes A, B, C, D, E to create concepts *C_i
***E_k* is element k of an attribute**

Figure 9. Examples of the creation of augmented isomorphic permuted experimental designs that include permutations of both attributes and elements. (Source: created by the author).

For Set 2, not only is the order of the categories different (B, E, C, A and D) but the elements are also randomized in each attribute. The same experimental unit applied to the new set (virtual attributes and elements) would produce another concept:

$$C_i^2 = \{B_2|E_1|C_1|A_1|D_4\}\,. \tag{6}$$

For Set 3, the resulting concept is:

$$C_i^3 = \{C_4|A_3|D_4|E_1|B_3\}\,. \tag{7}$$

Further in the text the term IPED is applied to the augmented IPEDs.

In case of a number of elements exceeding the capacity of the design selected, it is possible to apply the same design iteratively to parts of the attributes and elements thus allowing for testing of different configuration of the attributes and elements. To achieve this, two new data objects are introduced to the model: *attribute utilization array W_c:*

$$W_c \equiv (w_1, w_2, \ldots, w_n) \tag{8}$$

and *elements utilization matrix* M_e:

$$M_e \equiv \begin{bmatrix} e_1^1 & e_1^2 & e_1^3 & \ldots & e_1^m \\ e_2^1 & e_2^2 & e_2^3 & \ldots & e_2^m \\ e_3^1 & e_3^2 & e_3^3 & \ldots & e_3^m \\ \ldots & \ldots & \ldots & \ldots & \ldots \\ e_n^1 & e_n^2 & e_n^3 & \ldots & e_n^m \end{bmatrix}, \tag{9}$$

where w_i is attribute utilization frequency (how many times attribute i has been selected in the permutations); e_i^j is elements utilization frequency (it keeps the number of times element j of attribute i has been utilized); $m = max_i\, A_i$ – the largest number of the elements in the attributes $A_1, A_2, \ldots A_n$ (the empty cells are padded with zeros up to the maximum size of m).

When the number of attributes exceeds the number of variables in the underlying experimental design, the design needs to be applied multiple times. In the first iteration, a random subset R_1 of attributes A is chosen: $R_1 \subseteq A$. The elements of the array W_c corresponding to the selected attributes are adjusted (incremented to reflect the utilization of the attribute in the iteration). This means that if attribute A_j has been selected for the current iteration (permutation) of the experimental design, then $w_j = w_j + 1$. After all the experimental units of the current iteration have been used, a new selection of the attributes is executed:

$$R_2 \subseteq A, \tag{10}$$

where $R_1 \neq R_2$ if the size of the design does not exactly match the size of the project.

This process continues until all attributes are tested. During the selection process for R_2 (and following iterations if required), array W_c is checked to balance utilization of the attributes. In the ideal case, every attribute should be selected an equal number of times across multiple iterations of the experimental design. In reality, the process aims to minimize the standard deviation of the number of tested attributes contained in the array W_c:

$$\sigma_c = \min \sqrt{\frac{1}{\mathrm{n}} \sum_{i=1}^{n} (w_i - \bar{w})^2} \tag{11}$$

where $\bar{w}$ is mean of attribute utilization array elements.

For practical purposes (software implementation), (11) could be simplified as the following:

$$\chi_c = min \sum_{i=1}^{n} (w_i - \overline{w})^2 \quad (12)$$

where χ_c is a minimization criterion for selecting attributes in IPED.

A similar approach is applied when the number of elements in the attributes exceeds the number of the levels in the experimental design. In the first iteration, a random subset of elements E_1^i in each attribute *i* is chosen:

$$E_1^i \subseteq A_i \,, \quad (13)$$

where A_i is a full set of the elements in attribute *i*.

The elements of the matrix M_e corresponding to E_1^i are adjusted (incremented to reflect the utilization of the element in the run). This means that if the element a_i^j (element *j* in attribute A_i) has been selected for the current iteration of the experimental design to the array E_1^i, then $e_i^j = e_i^j + 1$ (incremented by 1).

After all the experimental units of the current iteration have been used, a new selection of the attributes is executed:

$$E_2^i \subseteq A_i, \quad (14)$$

where $E_1^i \neq E_2^i$.

This process continues until all elements are tested. During the selection process for E_2^i (and following iterations if required by the specific set of elements), matrix M_c is checked to balance utilization of the elements. In the ideal case, every element should be selected an equal number of times across multiple iterations of the experimental design. It is quite difficult to achieve that if the attributes have unequal sizes. In that case, the process aims to minimize the standard deviation of the tested elements distribution for each row of the matrix M_c (elements of the same attribute). For the row *c* (attribute *c*):

$$\sigma_e^c = min \sqrt{\frac{1}{m_c} \sum_{i=1}^{mc} (e_c^i - \overline{e_c})^2} \quad (15)$$

For practical purposes (software implementation), (15) could be simplified as the following:

$$\chi_e^c = min \sum_{i=1}^{mc} (e_c^i - \overline{e_c})^2 \quad (16)$$

where χ_e^c is a minimization criterion of selecting elements into IPED; $\overline{e_c}$ is mean of the row *c* of matrix elements utilization M_e; m_c is the number of elements in attribute *c*.

Furthermore, if the elements have some constraints (mutual restriction, e.g., cannot appear together due to semantic or technological incompatibility), a new data object, *elements constrains matrix,* is introduced:

$$
\begin{array}{c|ccccccccccc}
 & \boldsymbol{C_1^1} & \cdots & \boldsymbol{C_{n1}^1} & \boldsymbol{C_1^2} & \cdots & \boldsymbol{C_{n2}^2} & \cdots & \boldsymbol{C_1^k} & \cdots & \boldsymbol{C_{nk}^k} \\
\hline
\boldsymbol{C_1^1} & 0 & 0 & 0 & r_{11}^{21} & \cdots & r_{11}^{2n2} & \cdots & r_{11}^{k1} & \cdots & r_{11}^{knk} \\
\vdots & 0 & 0 & 0 & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\
\boldsymbol{C_{n1}^1} & 0 & 0 & 0 & r_{1n1}^{21} & \cdots & r_{1n1}^{2n2} & \cdots & r_{1n1}^{k1} & \cdots & r_{1n1}^{knk} \\
\boldsymbol{C_1^2} & r_{21}^{11} & \cdots & r_{21}^{1n1} & 0 & 0 & 0 & \cdots & r_{21}^{k1} & \cdots & r_{21}^{knk} \\
\vdots & \cdots & \cdots & \cdots & 0 & 0 & 0 & \cdots & \cdots & \cdots & \cdots \\
\boldsymbol{C_{n2}^2} & r_{2n2}^{11} & \cdots & r_{2n2}^{1n1} & 0 & 0 & 0 & \cdots & r_{2n2}^{k1} & \cdots & r_{2n2}^{knk} \\
\vdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & 0 & \cdots & \cdots & \cdots \\
\boldsymbol{C_1^k} & r_{k1}^{11} & \cdots & r_{k1}^{1n1} & r_{k1}^{21} & \cdots & r_{k1}^{2n2} & \cdots & 0 & 0 & 0 \\
\vdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & 0 & 0 & 0 \\
\boldsymbol{C_{nk}^k} & r_{knk}^{11} & \cdots & r_{knk}^{1n1} & r_{knk}^{21} & \cdots & r_{knk}^{2n2} & \cdots & 0 & 0 & 0
\end{array}
\tag{17}
$$

where C_j^i is the element *j* of the attribute *i* (the first row and the first column, shaded, are shown as captions); r_{xy}^{uv} is a restriction between the element *v* of the attribute *u* and the element *y* of the attribute *x*.

This matrix, in most cases, either is empty (no constraints) or sparsely populated. If some elements cannot appear together, they could be restricted in the design. This means that during the process of element selection the elements constrains matrix is applied to each new elements (and if needed attributes) selection and the randomization is performed until the constrains are satisfied. The elements in the same attribute are always restricted each to another as no two elements from an attribute could appear together in one concept.

It is possible to accommodate attribute level constraints as well by introducing *attributes constraints matrix*:

$$
\begin{array}{c|cccc}
 & \boldsymbol{C_1} & \boldsymbol{C_2} & \cdots & \boldsymbol{C_n} \\
\hline
\boldsymbol{C_1} & 0 & v_1^2 & \cdots & v_1^n \\
\boldsymbol{C_2} & v_2^1 & 0 & \cdots & v_2^n \\
\cdots & \cdots & \cdots & 0 & \cdots \\
\boldsymbol{C_n} & v_n^1 & v_2^2 & \cdots & 0
\end{array}
\tag{18}
$$

where $\boldsymbol{C_i}$ is the attribute *i*; v_j^i is the restriction between attributes *i* and *j*.

If two attributes are restricted, they can't appear together. This means that the attribute selection step should be repeated until the unrestricted attributes are selected. Of course, the number of attributes in the project should be larger than the number of the variable in the experimental design. Otherwise, any restriction would fail the design creation project.

In the majority of cases, the projects are executed without the restrictions to avoid the complexity of setting and satisfying the constraints. In addition, any constrain would make the experimental design less robust so they should be considered during the analysis stage rather than during the data collection.

The statistical models described in this section create multiple IPEDs for each individual respondent providing the following benefits:

- elimination of bias of selection
- homogeneous testing of the elements of the conjoint analysis ensuring multiple exposure of each possible combination of the element to the respondents (with a reasonable number of respondents)
- facilitates detecting and estimation of the interactions between the elements (including the higher order interactions – described in the next section)
- facilitates segmentation of the respondents based on the patterns of their responses.

The permuted designs are pivotal to the ability to detect any and all interactions, utilized in this dissertation. Due to the randomized permutation of the design, IPED could create hundreds of isomorphic executions that are unique (up to statistically possible in a specific design). In result, a sufficiently large sample of respondents could test every possible pairwise combination (and higher order interactions) of the elements multiple times thus creating an opportunity to analyze their contribution to the additive model through a regression. The details of the methodology are described in the Study I.

1.2.2. Interactions in Concept Testing

In conjoint analysis, interactions occur when the combined effect of two attributes is different from the sum of their two main effect utilities. Despite of progressively more sophisticated research of interactions such as presented in Green and Rao (1971), Green (1973), Green and Wind (1973), Wilkie and Pessemier (1973), Aiken and West (1991), Ross and Creyer (1993), Ping (1995), Chrzan and Orme (2000), Overton (2001), Toubia et al. (2003), Lusk and Norwood (2005), Yu, Goos and Vanderbroek (2007), the issue is still not completely resolved for larger scale projects like the ones addressed in the thesis.

According to Carroll and Green (1995) and Lusk and Norwood (2005), a majority of conjoint analysis approaches to consumer preference measurement emphasize non-interactive models of either additive or multiplicative nature. For the total utility for multi-attribute alternative, according to Green and Devita (1975), that could be described as an *n*-component array:

$$x = (x_1, x_2, \dots, x_n), \tag{19}$$

a non-interactive additive model could be defined as shown in equation (1).

As initially pointed out by Green and Devita (1974), situations can arise in which it is reasonable to assume that the utility of a multi-attribute item is based on a more complex model. This was further developed in Hayduk and Wonnacott (1980) which suggested that situations can arise in which we would like to consider interactions among factors (elements). Aiken and West (1991) defines interactions as a statistical problem commonly faced by researchers in many fields: how to structure, test, and interpret complex multiple regression models contacting interactions, curvilinear effects, or both.

The term interaction may be defined in one of two different ways – explicit interactions (synergisms, suppressions) and implicit interactions.

Explicit interactions are pairs of elements whose combination generates a statistically significant term in a regression equation or in analysis of variance. Generally, interactions manifest themselves quantitatively in analysis of variance or regression once the proper mathematical expression has been made. For example, in regression analysis, we can create an equation, which relates the presence/absence of two variables (A, B) to a rating R:

$$R = k_0 + k_1 A + k_2 B + k_3 (AxB), \tag{20}$$

where k_0 is a constant of the regression, k_1 and k_2 are utilities (regression coefficients) of the elements A and B.

The equation (20) shows how to estimate the magnitude of the rating from knowing the values of two variables (A, B). In addition, an interaction term AxB can be inserted into the equation to account for variations in ratings introduced by the combination of elements. Through regression modeling, the significance of the interaction term AxB could be determined. In the context of dummy variable matrix, AxB should be viewed as multiplication of 'present' ('1') and 'absent ('0') values. If the term AxB is significant then the variables A and B interact with each other. If the interaction is significant, and the coefficient of that interaction k_3 is positive, then we conclude that A and B act *synergistically* (adds an additional value k_3 to the sum of k_0, k_1 and k_2). If the coefficient k_3 is negative, the value k_3 is subtracted from the expected sum of the utilities A and B. In that case, there is a *suppression* between A and B. The values k_0, k_1, k_2 and k_3 must all be determined by regression.

Finkbeiner and Pilar (1991), Carroll and Green (1995), Lusk and Norwood (2005), Hayduk and Wonnacott (1980) point that the majority of the current approaches assumes that there are no interactions between the elements and thus the additive model $U(x)$ could be presented a simple as shown in equation (1).

Chakraborty et al. (1991, 1992) addresses the issue of screening for interactions between design factors and demographics although limited to choice-based conjoint analysis and on a very restricted basis. Aiken and West (1991) refers to some conjoint analysis approaches that allow for a pre-selected list of anticipated interactions to be included in the test. Such alleged interactions become an integral part of the experimental design and are tested along with the individual elements. In that case, the additive model could be modified as the following:

$$U(x) = const + \sum_{i=1}^{n} b_i x_i + \sum_{i,j \in \gamma}^{n} c_{ij} x_i x_j, \tag{21}$$

where c_{ij} are interaction coefficients between elements x_i and x_j (i, j = 1 to n; i and j do not belong to the same attribute) and γ is a subjectively pre-selected subset of elements interactions.

The additive model $U(x)$ that accounts for all possible pairwise interactions between the elements in conjoint analysis could be described with the following equation:

$$U(x) = const + \sum_{i=1}^{n} b_i x_i + \sum_{i,j=1; i \neq j}^{n} c_{ij} x_i x_j, \tag{22}$$

where c_{ij} is interaction coefficient between elements x_i and x_j (i, j = 1 to n; i and j do not belong to the same attribute).

Aiken and West (1991), following Campbell and Stanley (1966), infers that a straightforward approach for orthogonal estimation of all possible interactions (two-factor, three-factor, and so on) would call for a full factorial design. For realistically sized problems relevant to NPD, the number of combinations generated would be prohibitively large for respondent evaluation thus limiting practical usability of the approach.

Green (1973) suggests a method for estimating the third order interactions (interactions between the triads of elements) although its practicality is limited to very small sets of elements due to computational complexity and imposed assumptions.

A model that accounts for all interactions of the third order could be described with the following formula:

$$U(x) = const + \sum_{i=1}^{n} b_i x_i + \sum_{i,j=1; i \neq j}^{n} c_{ij} x_i x_j + \sum_{i,j,k=1; i \neq j \neq k}^{n} c_{ijk} x_i x_j x_k \tag{23}$$

where c_{ijk} is interaction coefficient between variables x_i , x_j and x_k (i, j, k = 1 to n; i, j, k do not belong to the same attribute).

The model for the interaction model of the order r could be described with the following formula:

$$U(x) = const + \sum_{i=1}^{n} b_i x_i + \sum_{i_1,i_2=1;i_1\neq i_2}^{n} c_{i_1 i_2} x_{i_1} x_{i_2} + \dots + \sum_{i_1,i_{2,\dots,}i_r=1;i_1\neq i_2\neq\cdots i_r}^{n} c_{i_1 i_{2\dots} i_r} x_{i_1} x_{i_2} \dots x_{i_r} \quad (24)$$

where $c_{i_1 i_2}$ is interaction coefficient of the second order between variables x_{i_1} and x_{i_2} (i_1, i_2 = 1 to n; i_1, i_2 do not belong to the same attribute); $c_{i_1 i_{2\dots} i_r}$ is interaction coefficient of the order r between variables $x_{i_1} x_{i_2} \dots x_{i_o}$; i_1, i_2 ,... i_r do not belong to the same attribute).

The current dissertation researches only the second order of the interactions as the most practical application of the approach although the underlying foundation is generalized and could be utilized to detect any and all higher order interaction with a sufficient number of experimental design permutations.

Fractional factorial designs, in which one can estimate a limited number of interactions that are free from confounding with main effects, represent a possible solution. However, points out Green and Devita (1974), the number of combinations becomes unwieldy in problems of realistic size. Green and Devita (1975) modified the approach by structuring the test in two sections: first respondents evaluate all possible pair-wise interactions and then perform a standard conjoint analysis exercise. In case of n attributes (factors) with m elements (levels) in each, the first step alone would require R ratings, where

$$R = [n*(n-1)/2] * m, \quad (25)$$

which is still an unreasonably long exercise for practical purposes.

Figure 10 shows a conceptual model of the explicit interactions. This approach, further described in Study I, is based on the U.S. Patent Application Serial No. 11/032,834 (Moskowitz and Gofman, 2005). In a conjoint analysis project with p attributes A_1 to A_p, each containing elements A_{k1} to A_{kl}, some of the interactions could be foreseen or pre-selected for testing (depicted in solid lines). During the test, these interactions are incorporated into the experimental design and tested by the respondents.

A latent interaction (for example, the one depicted in a dash-line between A_{pl} and A_{2m}) represents an existing interaction that could not be predicted by the expert to include into the design or missed by chance. If it goes undetected, this interaction could lead to providing NPD with misleading results missing an important information about a possible synergy or suppression between the features.

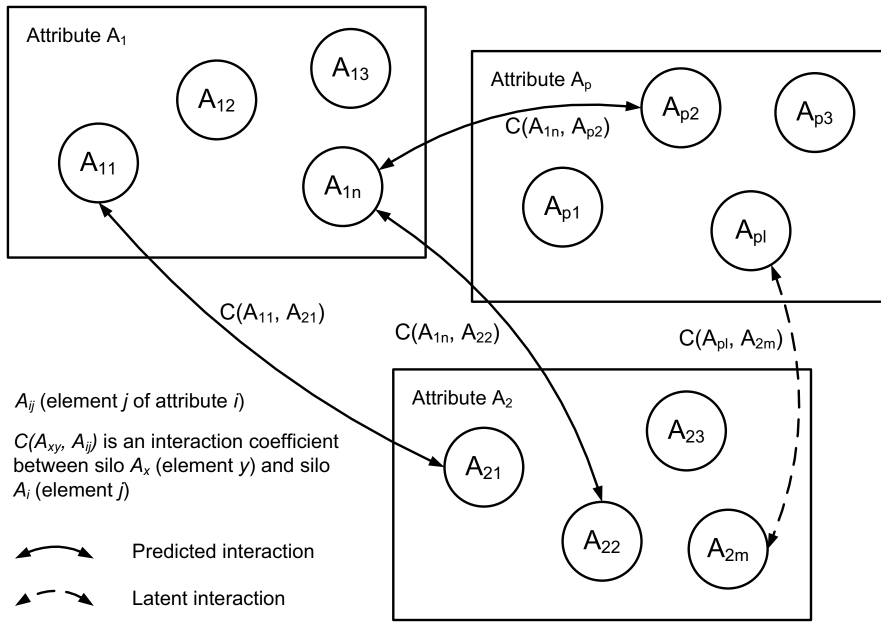


Figure 10. Conceptual model of explicit interactions. (Source: compiled by the author).

Table 3 shows an example (partial) of the dataset utilized for detection of the explicit interactions. This sample conjoint analysis project consists from six attributes (A-F) with four elements in each.

Each row in Table 3 describes a concept seen by a respondent. The data is prepared for the dummy variable regression with '1's representing present elements and '0's depicting the absent elements. Most of the numbers in each row are zeros because a concept does not contain most of the elements.

Although IPEDs facilitate individual models for each respondent for the analyses of predicted preferences and segmentations, interactions' modeling requires aggregate set of data (all the models across all the respondents are aggregated into one model). Each IPED contains a limited set of combinations. Every element appears several times in combinations with other elements. To detect possible interactions, the individual IPEDs are pooled together in one large dataset similar to that shown in Table 3 which typically would contain thousands of lines. Finally, each row contains the rating assigned by the respondent (1–9 scale).

Table 3. Example of a dataset (partial) used for explicit interactions detection proposed by the author with elements $A_1 \ldots F_4$ of attributes *A-F* (six attributes with four elements in each). (Source: compiled by the author).

A_1	A_2	A_3	A_4	B_1	B_2	B_3	B_4	C_1	C_2	C_3	C_4	D_1	D_2	D_3	D_4	E_1	E_2	E_3	E_4	F_1	F_2	F_3	F_4	RATINGS
0	0	1	0	0	0	1	0	0	1	0	0	0	0	1	0	0	0	0	1	0	1	0	0	5
0	0	1	0	0	1	0	0	0	0	1	0	0	0	0	1	0	0	0	1	1	0	0	0	4
0	0	0	1	0	0	0	1	1	0	0	0	0	0	1	0	0	0	0	1	0	0	0	1	9
0	0	1	0	0	0	1	0	1	0	0	0	0	0	0	1	0	0	0	1	0	0	1	0	6
0	0	0	0	0	1	0	0	0	0	1	0	0	1	0	0	0	0	1	0	0	0	0	1	5
0	0	0	1	0	0	1	0	0	0	1	0	1	0	0	0	0	0	1	0	1	0	0	0	5
0	1	0	0	0	1	0	0	0	0	1	0	0	0	0	1	0	0	0	1	1	0	0	0	6
0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	1	1	0	0	0	0	1	0	0	6
0	1	0	0	0	1	0	0	1	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	5
1	0	0	0	**1**	0	0	0	0	0	0	1	0	0	1	0	1	0	0	0	0	0	0	1	1
0	0	0	1	0	0	0	1	1	0	0	0	0	0	0	1	0	0	1	0	1	0	0	0	6
…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…
0	1	0	0	0	0	1	0	0	0	1	0	0	0	0	1	0	0	0	0	0	1	0	0	5
0	0	1	0	0	0	1	0	0	0	1	0	1	0	0	0	0	0	0	1	1	0	0	0	5
0	1	0	0	0	0	1	0	0	0	0	1	1	0	0	0	0	1	0	0	0	0	0	1	1
0	0	0	0	0	0	1	0	1	0	0	0	0	1	0	0	0	1	0	0	0	0	0	1	5
0	1	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	1	0	0	0	1	0	0	5
1	0	0	0	0	0	0	1	1	0	0	0	0	0	0	1	1	0	0	0	0	0	1	0	8
0	0	0	1	1	0	0	0	0	0	1	0	1	0	0	0	0	0	0	1	0	0	0	1	4
1	0	0	0	**1**	0	0	0	1	0	0	0	0	0	0	1	0	0	1	0	1	0	0	0	2
…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…

'1' if the element is present in a concept (row); '0' – if it is absent. Two highlighted rows show appearance of the same combination of elements (A1 and B1, in frames).

To detect the explicit interactions, the approach forces in the linear terms and subsequently allows additional terms, i.e., pairs with a synergy or a suppression, to enter the already-developed equation if those terms contribute significant additional predictability to the equation.

The criteria for entering the linear equation and adding additional terms can be made stringent or lax using the mechanics of stepwise multiple linear regression (SPSS, 2007). With a stringent criterion, very few additional predictor terms will enter the equation. In contrast, with a lax criterion many additional terms will enter the equation. Study I describes the process in more details.

Implicit Interactions (scenarios) are the nature of responses when these responses are made within a certain set of conditions. In other words, implicit interactions are the effect of the conditions on some dependent variables (e.g., the performance of the features of a researched product as a function of other elements). Figure 11 shows a conceptual model of implicit interactions. An attribute A_p selected as a pivotal one (e.g., brands, key features) drives the utilities of the rest of the attributes. If the pivotal attribute A has m elements, then there are m possible scenarios. In a conjoint analysis with total of N elements, for an element A_i, the scenario will analyze the utilities of the elements x_j^{pi} (where $j = 1 \ldots n$; $n = N - m$) creating an n-component utilities array X^{pi}:

$$X^{pi} = (x_{\mathbf{1}}^{pi}, x_2^{pi}, \ldots, x_{\boldsymbol{n}}^{pi}). \quad (26)$$

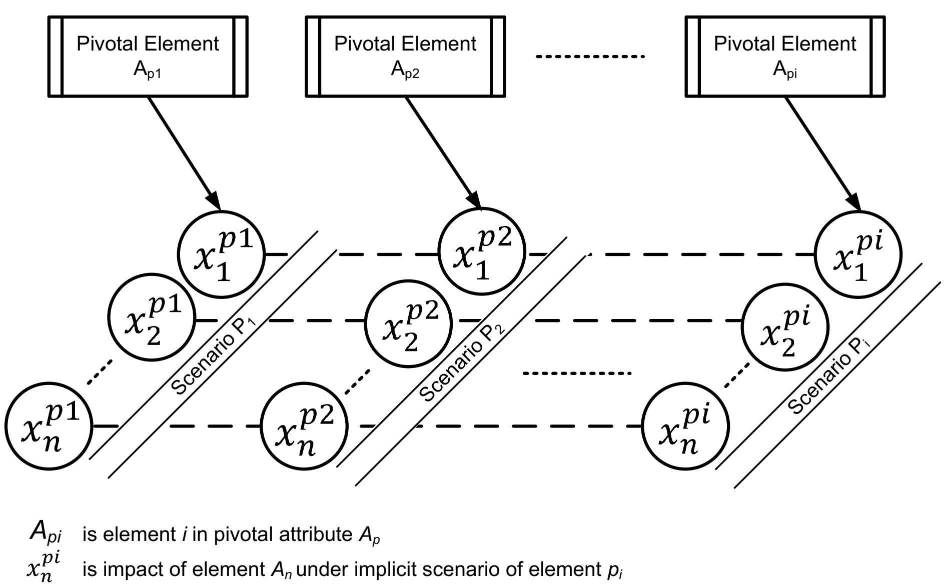


Figure 11. Conceptual model of implicit interactions. (Source: compiled by the author).

Selection of another pivotal element will lead to a new, distinct scenario with a unique array of utilities for this implicit interaction (scenario). By comparing the performance of utilities under different pivoting elements, a researcher could have valuable input in the process of selecting features for NPD.

The process of estimating the implicit interactions is different from the one described above for the explicit interactions. If the attribute A is selected as a pivotal one, we can choose any of the elements in that attribute and select only the cases where this element was present (the cells in the appropriate column in Table 3 are equal to 1).

By repeating the selection process for every element in the chosen attribute, the researcher splits the whole data set into several different layers. For E elements in an attribute (e.g., attribute A), there will be $(E+1)$ layers – one per each element in the attribute and one for cases when the attribute is absent, because the experimental design is set up so that some of the concepts are missing elements from the particular attribute.

The working dummy variable matrix for each pivoting element A_{pi} contains cases (rows) where $A_{pi} = 1$. The matrix includes all of the elements except the pivoting category used to create the stratum. A separate regression model for each stratum relates the presence/absence of the elements to the rating values. If attribute A is chosen as a pivotal one, the regressions of the working matrixes relate the presence/absence of $B_1 \ldots F_4$ to the ratings (e.g., interest in the product) for each of the elements in the attribute A. There would be $C * E = 20$ independent variables. There would be five such regression equations, one for each value of A plus one regression when no elements from attribute A are present at all. Implicit interactions show how each of the elements in attribute A 'drives' the utilities of the remaining elements.

If attribute A, a key ingredient of a product during NPD for example, has been selected as a pivotal attribute, then the researcher could uncover how other elements of the project perform if the concept is identified with a specific key ingredient.

Furthermore, as noted above, since the respondent evaluates all of the elements against all of the other elements in a randomized fashion, the respondent does not have an opportunity to associate the concept study with a particular ingredient name. The same thinking holds for analyses by other attributes.

In fact, a complete analysis of the scenarios would present separate regression analyses for each element in each attribute. For C equally sized attributes, and E elements per attribute this complete analysis would generate $C * (E + 1)$ regression models. In the case of six attributes with four elements in each one, there would be $6 * 5 = 30$ regression models. By looking at each set of regression models, one per attribute, the researcher would be able to identify the implicit interaction effects of each element with every other element in a different attribute.

Appendix B (Table A-2) has sample results of estimating of implicit interactions for the brands of food companies. The approach is discussed in more detail in Study I. The proposed IPED approach expands the theory of experimental design and facilitates creation of multiple isomorphic designs that enhance the ability of conjoint analyses to estimate predicted consumer preferences among the features of new products. IPEDs eliminate the bias of the limited set of the combinations of the elements characteristic to the majority of the experiment design-based methods. In addition, by creating a large number of isomorphic designs IPEDs enable testing any and all interactions between the elements allowing detection of all explicit interactions and providing the developer with additional information, not available with the traditional methods, in the form of scenarios (implicit interactions). An added benefit of the IPEDs is the ability to segment consumers based on the patterns of their individual utilities which is one of the most targeted ways of understanding the consumer, as shown in Lee et al. (2007), thus opening new opportunities, especially in mature food categories notorious for intrinsic difficulties in finding ways for innovation.

1.2.3. Exploring New Approaches in Consumer-Driven NPD: Rule Developing Experimentation

Addressing the opportunities identified earlier, the dissertation concentrates on the stages 3 and 4 and partially on stage 1 (Figure 3) of the NPD process. This section is a formalization of the author's works to create a generalized framework for a conjoint analysis-based research approach that could be applied to NPD in mature food categories as well as other areas. The framework is partially based on the U.S. Patent 6,662,215 B1 (Moskowitz and Gofman, 2002). It integrates proposed modifications to experimental design and conjoint analysis. This methodology (or its parts) has been utilized in the Studies I-III of this dissertation for empirical studies.

Rule Developing Experimentation (RDE) is a methodology of structured consumer-based experimentation with conceptual prototypes which is applicable to NPD and other areas. From a classification point of view, RDE is derived from the consumer-driven proactive approaches to structured experimentation researching consumer preferences on the concept level utilizing partial profile conjoint analysis with incomplete concepts based on a special type of fractional main effects experimental designs (isomorphic permuted experimental designs). RDE analyses pattern-based latent segmentation along with detecting explicit and studying implicit interaction.

In a wider business meaning, RDE is a systematized solution-oriented business process of experimentation that designs, tests, and modifies alternative ideas, packages, products, or services in a disciplined way using experimental design, so that the developer and marketer discover rules and patterns showing what appeals to the customer, even if the customer can't articulate the need, much less the solution (Moskowitz and Gofman, 2007).

Figure 12 shows the conceptual map of RDE. The input materials are organized into attributes and elements, arranged into experimentally designed concepts based on IPED. The process starts partially with the same sources of initial ideas as in traditional approaches. In addition, it could use data store containing structured information created by previous utilization of RDE due to RDE ability to accumulate and compare data across the projects. The initial ideas are formatted into concise descriptive snippets of text or other media creating individual elements of the products grouped into attributes of similar features.

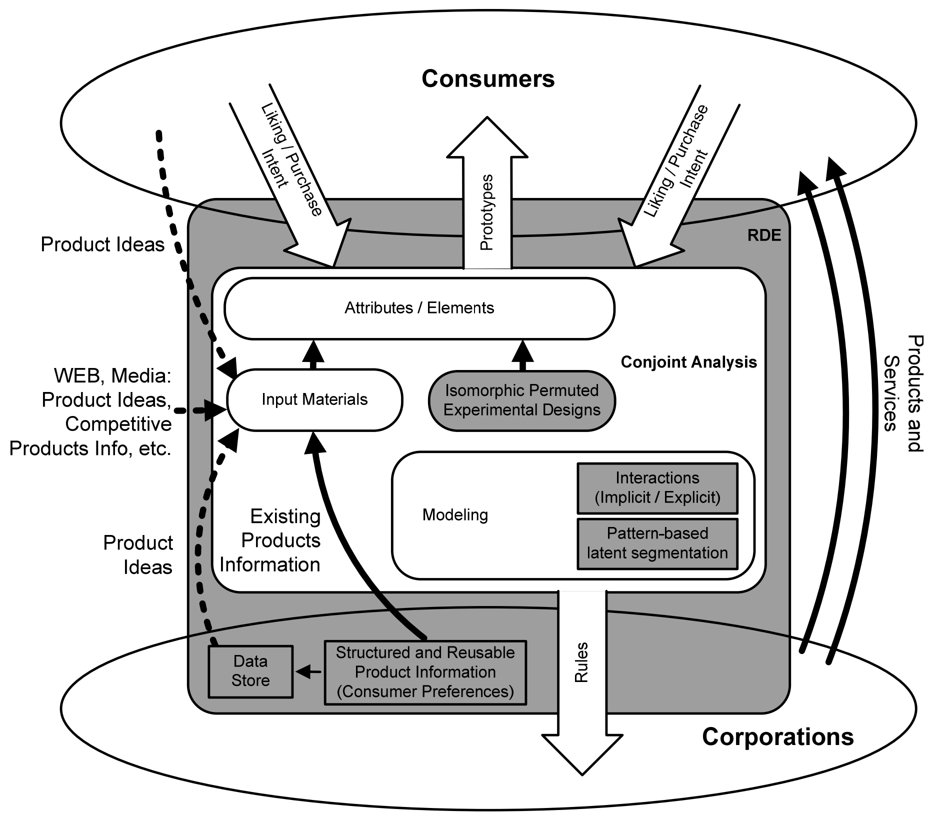


Figure 12. Conceptual map of the modified conjoint analysis – Rule Developing Experimentation (RDE). The proposed modifications to the conjoint-analysis based consumer-driven approach to product development are highlighted (shaded areas) (Source: created by the author).

The attributes (groups of elements) separate the elements into similar groups such as product features, benefits, emotional messages. These elements are combined into the sets of concepts. The combinations creation is enabled by IPEDs thus facilitating individual (for each respondent) unique sequences of concepts (subject to statistically possible limits depending on the number of the categories and elements). With a sufficient number of respondents, the proposed individual IPEDs facilitate the testing of every possible combination of the elements multiple times by different respondents within conjoint analysis, including the higher order interactions.

This creates a platform of concepts testing in widely varied contexts of different combinations of the elements that leads to interaction detection and analysis as well as pattern-based latent segmentation. The IPEDs also enable conjoint analysis to estimate the absolute values of the utilities rather than the relative values characteristic to the most existing methods. These concepts are presented to a representative group of consumers (respondents) or other stakeholders to elicit their preferences (e.g., their purchase intent, liking, preference or choice).

The solicited ratings are combined with the underlying IPEDs and are analyzed through a regression analysis, imputing the contribution of each individual element to predicted consumer preferences and thus creating individual sets (for each respondent) of the utilities (part-worth contributions) of the elements.

This in turn enables RDE to detect pattern-based latent segments of the consumers based on the similarities in the patterns of the utilities. As argued by several scholars (Green, and Krieger, 1991; Neal, 2003; Beckley et al., 2007; Moskowitz et al., 2005), the segmentation of the consumers based on the similarity of their responses is more targeted for NPD than traditional demographic grouping. IPED foundation of RDE facilitates this process along with detecting any and all explicit interactions between the elements and analysis of implicit interactions, which is not practically feasible in the existing methods.

The resulting quantitative relationships between the elements and consumer preferences (rules) could be utilized by the corporations to provide directions of how to increase consumer liking (purchase intent) under different scenarios. RDE quantifies the most likely combinations of ideas (features or messages) that may be acceptable to the consumer.

RDE encompasses six basic steps, which partially incorporate steps usually used in conjoint analysis projects although in a modified form (see Appendix C, Figure A-1) extending the approach to different fields:

Step 1. Preparing raw materials. Identification of groups or classes of features that constitute the target product (offering, product, service) For example, in the case of a credit card offer, among the tested features could be annual percentage rates (APR) and rewards options. Every such attribute of ideas comprises several elements (different levels of APR or various reward options).

Step 2. Creating test concepts. Process of mixing and matching the elements according to an experimental design to create a set of concepts. The second step is based on a variation of conjoint analysis (partial profile with incomplete concepts based on individual models afforded by IPEDs).

Step 3. Collecting data with the consumers. The actual experimentation with the consumers soliciting their responses to experimentally designed concepts.

An example of a rating question: "How likely would you be to buy this product?"

Step 4. Analyzing results. One of the key differentiating features of RDE is individual models of utilities for each respondent. This allows patterns discovered in the data, across elements and respondents (more in Step 5), to generate rules for more targeted optimization as well as uncover all meaningful two-way interactions between the elements. In addition, the ability to estimate absolute values of the utilities in RDE allows for databasing the results. The database makes for meaningful comparison of the element utilities in one study, and across studies, which then track the consumers' preferences across studies and longitudinally.

Step 5. Identifying pattern-based latent segments. As proved in Green, and Krieger (1991) and Neal (2003), people's preferences differ regardless of demographic group. RDE identifies naturally occurring pattern-based latent segments of the population that show similar patterns of the utilities utilizing IPEDs. The approach of dividing people differs very much from the conventional ways that use gender, income, products purchased and the like.

Step 6. Applying the generated rules to create new products, services, offerings. Utilization of the results of RDE to 'optimize' the ideas in the concepts creating a set of quantitative relationships between the elements of RDE and consumer preferences and directions of how to increase consumer liking. The best combination of elements are the ones that have the highest sum of utilities, including linear and interaction coefficients.

Figure 13 shows the generalized model of the RDE process. It starts with collecting of the input materials for NPD, which might come from corporations and consumers as well as from other places (such as database of the existing features, competitive analyses and consultants).

The input material is sorted into groups (attributes) of related features and an experimental design is applied to mix and match the elements to create individual (per respondent) designs through the permutation process of the underlying experimental design (IPED). Then the concepts are shown to the consumers with the help of Computer Aided Personal Interviewing (CAPI) system. Thornton and Hufflett (2005) describes the general process of utilizing Internet for interviewing in form of Computer Aided Web Interviewing (CAWI). The respondents rate the unique (up to statistically possible, depending on the design and the sample size) sets of individually created concepts on one or several rating questions. The collected data is analyzed resulting in individual regression models and pattern-based latent segmentation. During analysis RDE also detects any and all interactions between the elements.

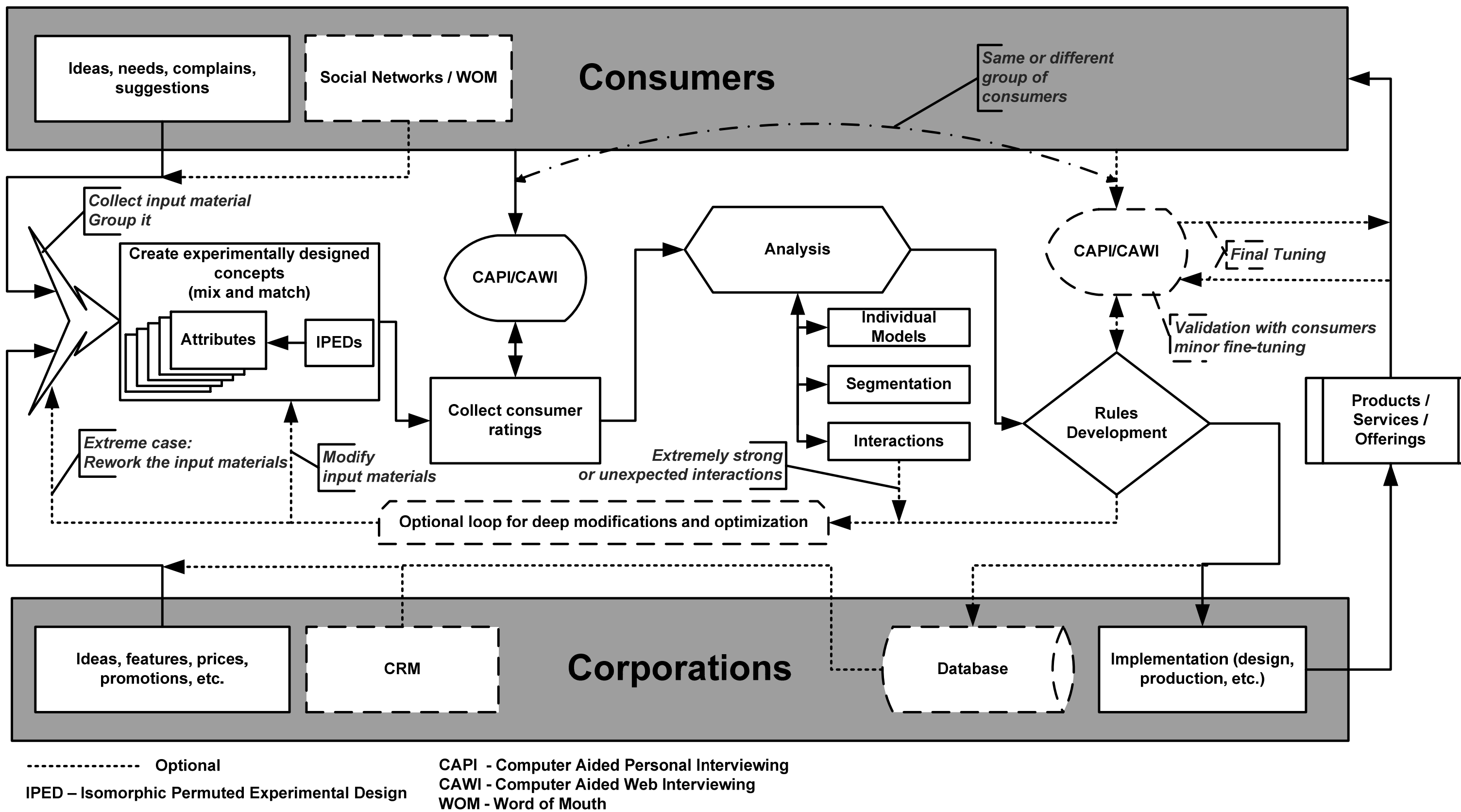


Figure 13. Rule Developing Experimentation (RDE) as applicable to NPD. (Source: created by the author partially based on Moskowitz, H.R., and Gofman, A. 2002. System and method for content optimization. U.S. Patent 6,662,215 B1, 16PP).

In case of highly unusual interactions or when the results are completely unexpected or suggest a radically new area of opportunities, the process might require iterative reworking of the input materials or additional fine-tuning. The results could be optionally validated / fine-tuned with consumers. During this process, several optimized (based on the maximum sum of individual utilities subject to existing constraints if any) concepts are tested with a set of respondents to validate and further tine-tune the results before implementation. The original group of respondents or different respondents could be invited for the validation. Optionally, the concepts could be analyzed in a qualitative session to better understand the consumer preferences.

Combined process facilitates a formalized approach with results pointing towards the most promising concepts for the total target population as well as demographic and pattern-based latent segments thus generating the input for NPD and design.

The next step is implementing the created rules for NPD. If the results do not solve the problem at hand, the process could be iterated.

Beckley et al. (2007) argues that the structure of RDE imposes the discipline of thinking resulting in a higher success rate than other methods. Just the process of preparing for RDE, agrees Lee et al. (2007), helps users better understand the problem and find possible solutions.

Beckley et al. (2007) and Moskowitz et al. (2005) point to some of the advantages of RDE:

- Pattern-based discoveries (segmentation) to facilitate more targeted optimization (pattern-based or latent segmentation).
- Discover any and all meaningful pair-wise interactions between the elements (including higher order interactions if needed).
- Analyze how one element 'drives' responses to another element using scenarios. A possible use of the implicit interactions in NPD is a "what-if" trade-off analysis of the effect of the replacing some consumer-preferred features with options that are more technologically or economically viable.
- RDE uses a variation of dummy variable regression to estimate the absolute values of the utilities, which in turn allows databasing the result for tracking the consumers' preferences and easy comparison of the utilities across the attributes.
- The individual models facilitate a parsimonious way to simulate market share and choice analysis.

An example illustrating an RDE implementation is shown in Appendix D.
An extension of RDE is utilized for sensory optimization (food ingredients) based on consumer taste testing of experimentally designed prototypes (Moskowitz et al., 2005; Gofman, Moskowitz, Mets, 2009b).

1.3. Validation Approaches and Implementation

1.3.1. Validation Approaches

The issue of validity of the methods for obtaining consumer preferences, including the validity of sample, questionnaire design, data, etc., have been extensively researched. Cronbach and Meehl (1955), Dillman (2000), Moskowitz et al. (2002), Redline and Dillman (2002), Rousseau and Sanders (2003) introduce and research a variety of methods that ensure valid input to corporate R&D and marketing.

RDE is based on conjoint analysis which in turn is founded on experimental design theory. Cattin and Wittink (1982) demonstrates that in experimental design, the effect of independent variables on a dependent variable is studied under controlled conditions, thus allowing for higher degrees of internal validity than, for example, single-case designs, such as researched in Atkinson and Donev (1992). To test the integrity of data, some traditional validations approaches use hold-out samples. As shown by Green, Krieger and Agarwal (1993), hold-out is a sample of observations withheld from estimation when multiple regression, discriminant function analysis, or any other type of analysis designed to yield a predictive model is being developed, so that the model's ability to predict future scores can be estimated by its ability to predict the data of the hold-out sample.

Another way of checking the quality of data analyzed in Moskowitz et al. (2002) is through the R statistic as a possible indicator of validity. If the respondent assigns the same number to every concept, then the R^2 value will be 0, because there will be no co-variation of the dependent variable with the independent variable. If, however, the respondent attends to all of the elements in a consistent fashion, argues Aiken and West (1991), then the R^2 will be high (with the maximum of 1). Moskowitz et al. (2005) and Gelman and Hill (2006) conclude that strategies in which the respondent attends to only a limited number of elements cannot yield high R^2 values, although these strategies may be consistently employed in an errorless fashion.

Many projects undergo the validation process when the synthesized 'optimized' concepts are tested in comparison with the existing offerings or competitive products as shown by Louviere (1988). The tests are usually conducted on the gestalts level in a simple rating survey for a short number of concepts or a choice exercise with select respondents. Some other projects are followed up with focus group discussions where the synthesized concepts or products are validated with the consumers, usually in comparison with the existing or competitive offerings. This validation for commercial projects is usually conducted by the end-client or an independent third party to ensure the integrity of the results.

One way to show validity of the RDE results is to use the model to estimate the likely rating for each concept. If possible, one should hold out a few concepts from the model, to show that the model can estimate concepts not used in creating the model. Another way is modeling the predicted utilities of concepts using the results of RDE and comparing them with the original ratings

(Figure 14). By knowing the features of the concepts, the researcher can use the model to estimate acceptance, even for combinations not directly tested. The results show high correlation of the measured and estimated values of the consumer ratings.

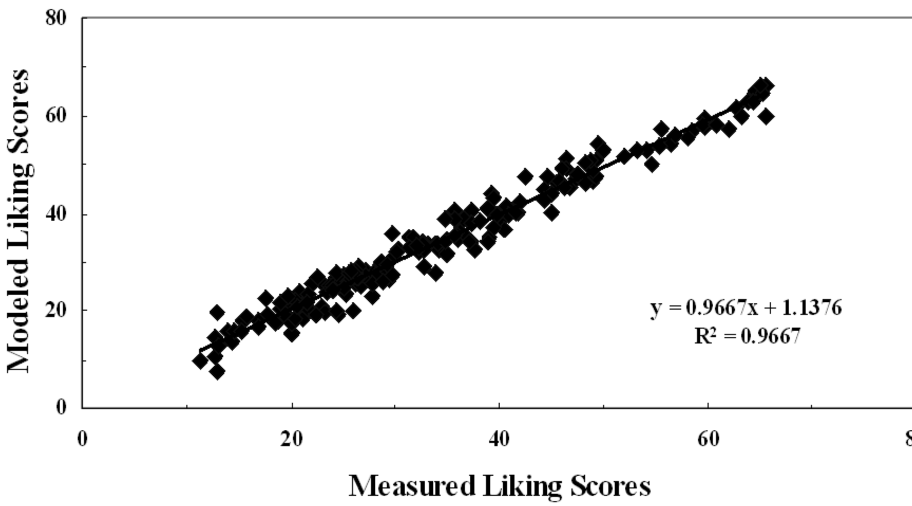


Figure 14. Example of the validation of RDE results by means of comparing the measured (actual) versus modeled (estimated) liking scores. The computed regression model accurately describes measured consumer liking (the goodness of fit statistics R^2 is close to 1). (Source: Moskowitz et al, 2005).

Other ways of validation used in a number of the RDE projects by the clients or a third parties involved testing of the synthesized concepts with a separate panel, focus groups discussions or with the market volumetric resulting from the launch of the product. Sapiro et al. (2005) describes a case when Unilever Brazil conducted an initial RDE-based concept development work. In the following months, Unilever executed a large scale validation process to define the suitability of the approach and the robustness of the results for possible wider future use. Over an extended period of time, split groups of consumers received different catalogs based on the RDE projects as well as a control group which had received the original catalog. Unilever tracked the activities of the consumers participating in the test including their actual purchases. The results proved that the experimental group exposed to the catalog based on the RDE results had substantially higher number of purchases over the period of research than the control group thus validating the approach.

The research projects initiated for the purposes of further developing the approach usually utilized a validation process when the 'best' concept (maximized predicted sum of utilities) was compared by the respondents with several concepts with lower predicted sum of utilities through direct ratings. Moskowitz, Graves, Cardello, and Lesher (1995), Moskowitz (2001), and Meiselman and Schutz (2003) describe one of the validations of the parts of RDE approach conducted by the US Army. The project has been supervised by Dr. Armand Cardello of the US Army Natick RD&E Center (Natick, Massachusetts). During this project, US Army Natick Laboratories used Ideamap® tool to test multiple ideas about soldiers' snacks. The following survey has been executed with the enlisted personnel. During the following validation process, the optimized soldiers' snacks have been generated based on the outputs of the RDE analysis and tested with the military personnel again. During the test, several newly synthesized products have been compared by the respondents (soldiers) with the existing products. The results have confirmed the validity of the conclusions (newly synthesized optimized products overwhelmingly won over the existing products).

Lee et al. (2007) describe another empirical approach that confirms the findings obtained by the RDE on the example of cereal.

In addition to being developed through direct cooperation with the Department of Marketing at Wharton School of University of Pennsylvania (Prof. Jerry (Yoram) Wind), different aspects of RDE and the approach itself have been reviewed and/or fine-tuned through cooperation with and input from a number of major universities.

1.3.2. Implementation

The results of the research presented in this dissertation have been implemented in algorithms and software tools. The most frequently used (at the time of writing of this dissertation) RDE tool is Web-based Software as a Service (SaaS) Ideamap.NET (www.ideamap.net), designed by the dissertant in cooperation with Wharton Business School of University of Pennsylvania as a continuation of his work on the original versions of Ideamap® and a PC-based conjoint analysis tool Ideamap® Wizard created by the dissertant earlier. Gofman (2005), Hartmann et al. (2004), Beckley et al. (2007), Lee et al. (2007) demonstrate Ideamap.NET application. It incorporates the described methods providing automatic permuted design creation, data collection, and analysis including segmentation. Appendix E (Figures A-2 to A-5) has screen captures of this tool (see an example of RDE implementation in Appendix D).

1.4. Structure of the Studies and Research Model

Based on the theoretical foundation researched in 1.2, the dissertation further examines RDE components and implementation. RDE is analyzed in the context of mature food categories which, in general, suffer from one of the highest new product launch failure rates in the industry. Studies I-III focus on the integral components of RDE: modified conjoint analysis based on IPEDs (researched in 1.2.1) and a new approach to detect and estimate interactions between the elements of conjoint analysis (introduced in 1.2.2). The approaches are demonstrated on several examples in mature food categories and cover screening/optimizing conceptual ideas of the products (Studies I-III), detecting explicit interactions (synergistic or suppressive) between the features/messages (Study I-III) as well as analyzing implicit interactions (Study I), followed by the steps to accumulate, aggregate and reuse consumer preferences data across the projects and products (Studies II and III). Study II introduces an integrated approach to aggregate sensory and conceptual information aiming to get even deeper consumer preferences understanding. Study III concludes the process by introducing an "innovation machine" to create new products in mature categories. All three studies utilize RDE tool Ideamap.NET described in 1.3.2.

STUDY I introduces two approaches to identifying the direction and magnitude of interaction between concept elements in a conjoint analysis task. Both approaches use main effects experimental designs, permuted to create hundreds of new designs isomorphic to the original design structure (IPEDs). In the first approach, the scenario analysis creates a distinct mutually exclusive and exhaustive set of subgroups from concepts with specific elements, runs a dummy variable regression within each subgroup, and identifies the effect of one element on the utilities of the others. In the second approach, the interaction analysis of a complete set of raw data forces in the linear terms for the single elements, and then allows significant pairwise combinations to enter if they contribute significant additional predictability to the model. The two approaches identify the existence of and then measure the utility of one element on the performance of others (scenario), and the unexpected effect of mixing two concept elements (interaction analysis). The approach is illustrated by two case histories: communicating the sensory and refreshing benefits of an orange beverage, and identifying the preferable features of a cookie.

STUDY II explores aspects and data for a tool-driven database that could be used for product development. The objective is to create a method whereby knowledge of concepts and products can be archived using overviews of a specific product category. The first phase of the database comprises systematic analysis of product concepts, which contain elements dealing both with features and emotions. The concept phase explores responses to statements about product features, emotional elements and brands aiming to develop a model showing how different concept elements (features) drive consumer interest.

The second phase comprises a sensory analysis of the competitive frame of products, even before systematic product development is initiated. This phase identifies expected and thus reasonable ranges of product-sensory features, levels of acceptance of typical products, relations between liking and sensory attributes and segmentation of sensory preferences. Together, the two phases could be used by product developers. The approach could be also used to archive current knowledge and facilitate data dissemination and sharing. The ultimate aim of both phases is to allow product development to become more based on common experience of the consumers rather than individual expertise of experts and thus more efficient, without compromising corporate knowledge of specific ingredients, processes or business opportunities.

The empirical part of the second phase of the study deals with the types of information that should be included in the structured database for NPD utilization, particularly in the mature food categories. The objective of this part of the study is to understand the drivers of liking for vanilla ice cream through obtaining consumer preferences on a representative selection of the category (22 vanilla ice creams varieties). This type of objective is a typical objective for category appraisal studies utilized on the initial stages of NPD.

STUDY III researches the process of innovating product features in categories typically considered to be mature. The unified structural approach and framework of RDE described above is utilized in this application. The analysis looks at what drives the consumers' preferences of the product features considered by developers. The research further identifies opportunities by both varying the respondent's task (rating on different end uses) and by using pattern-based latent segmentation to uncover new similarly minded groups of people where the actual identification of innovation opportunities emerge. The complete results of the study are presented in Appendix F (Table A-4). The source (original) experimental design utilized in Study III is shown in Appendix G (Table A-5).

Figure 15 shows the research model of the current dissertation. The three main parts of the model (Process, Applications and Foundation) are deeply connected in the research. Studies I-III explore at least two out of the three parts. The investigation of the other aspects of RDE has been presented in the Background of the Research section and in other publications of the author.

The foundation of RDE is based on conjoint analysis, pattern-based latent segmentation and the detection and analysis of interactions. These parts of the foundation are in turn based on the isomorphic permuted experimental designs.

The relationship between the foundation's blocks is researched in all three studies from different angles. The in-depth analysis of the foundation is provided in Study I. Study II researches the general framework of the RDE on an example of discovering opportunities for NPD in a mature product category. Study III continues this research and extends it into a formalized innovation process in NPD for mature product categories.

The RDE Process is represented by the six universal steps. The steps are explored in Background of the Research and Studies I–III. The research and other works of the author show the similarity of the framework and the necessary steps in a wide range of applications. Studies I–III show the process in the context of the examples of NPD in mature product categories. This includes research of the implicit and explicit interactions for NPD and pattern-based latent segmentation in mature categories (Studies I–III as well as the Background of the Research section). Study I explores in depth the new approaches to detecting interactions in conjoint analysis. The research shows the importance and methods of discovering any and all such interactions in the RDE process serving as a theoretical and methodological foundation of the approach. Studies I and II (and partially Study III) also address the utilization of the quantitative results of the research in form of a structural and reusable information of consumer preferences for NPD process.

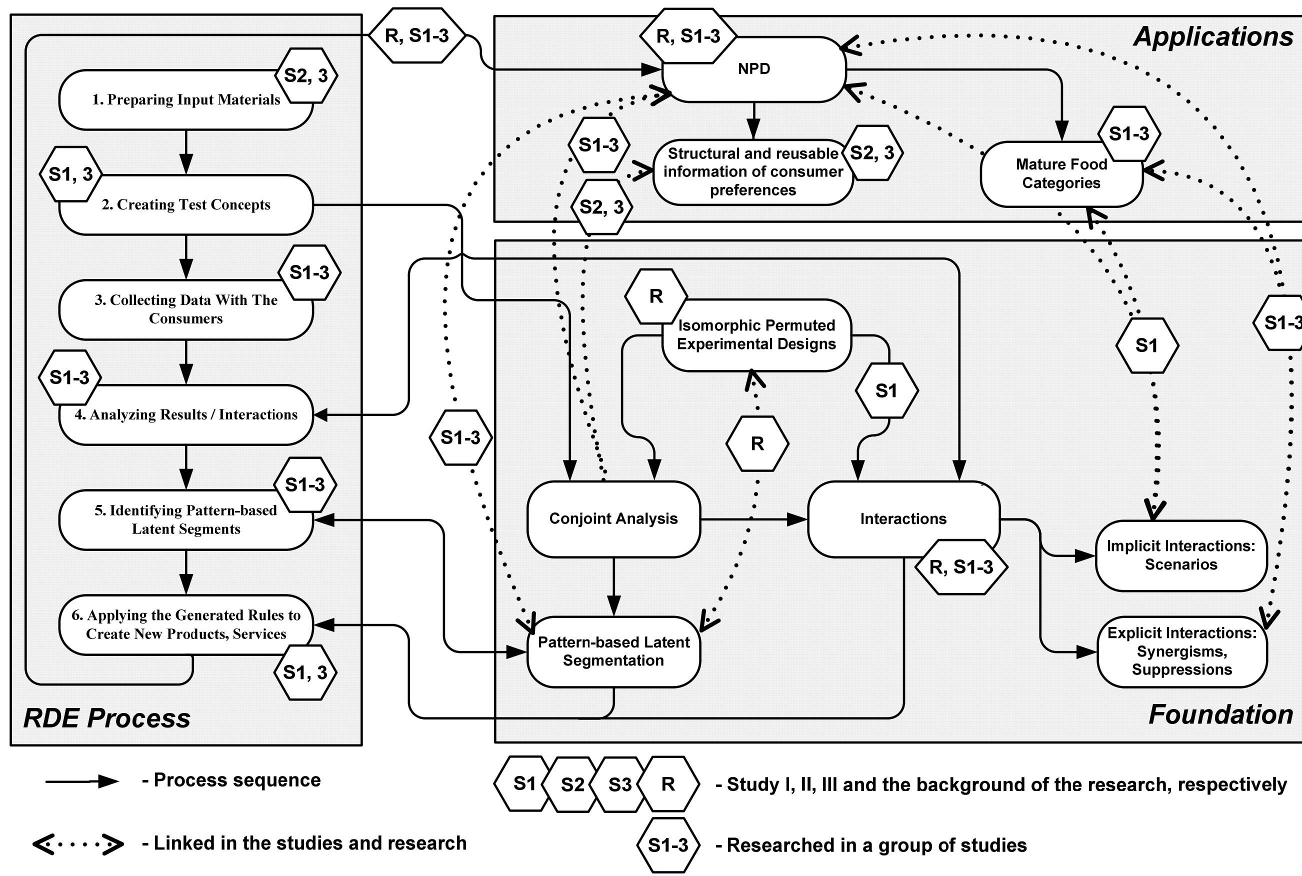


Figure 15. Research model – the proposed relationship between RDE Foundation, Process and Applications. (Source: compiled by the author).

The Foundation part is closely linked to the RDE Process (steps 1, 2, 4, 5, 6). All Studies research the Process steps. Studies II and III address in more details the Preparing Input Materials step. Creating Test Concepts, Collecting Data With The Respondents, Analyzing Results / Interactions And Identifying Pattern-Based Latent Segments steps are explored across all the Studies. The last step, Applying the Generated Rules to Create New Products and Services is researched in Studies I and III.

1.5. Research Methodology and Data Collection

Based on the research of the RDE methodology and its integral components summarized in section 1.2, the author conducted a series of empirical studies. The goals of the studies were to improve product development in mature food product categories and define the steps necessary for data accumulation, cross-project data comparison and reuse, as shown in section 1.4. The studies involved collecting and analyzing consumer preferences data utilizing the proposed methodologies.

The RDE methodology created a structure for the specific task (product features or messages) and then populated this structure with specific elements (features). For each of the studies, a group of consumers was invited to evaluate sets of experimentally designed concepts on an individual level and rate them on a scale (e.g., purchase intent). The process then modeled the results using a dummy variable regression analysis yielding the individual contributions of the elements to consumers' ratings and thus providing the input to NPD.

All three studies in this dissertation utilized Software as a Service application Ideamap®.Net™ which is an implementation (tool) of RDE for online consumer research (architectured and designed by the author and implemented under his management – see section 1.3.2).

For dataset one of STUDY I, 38 consumer respondents were recruited via an email invitation. The experimental design was permuted utilizing IPED methodology so that each respondent evaluated a different set of 40 combinations related to an orange beverage drink with a focus on messages with end benefits rather than with formulations.

The second dataset was obtained as part of a broader scale project on product innovation in the food categories. The ingoing objective was to identify how features of a typical mature food category, cookies, drive respondent interest. The study comprised six categories, each with six elements.

In contrast to the orange beverage study in dataset one, all of the six categories were "actionable", related to the formulations of the product, rather than the benefits messages of the first dataset. All of the elements could be used by a developer to create a new cookie product. The second dataset was based on the responses of 439 individuals randomly selected from the opt-in Moskowitz Jacobs Inc. Web panel. Each respondent evaluated 48 concepts, generating 21,072 concepts from which to analyze the scenarios and the interactions.

STUDY II explores consumers' preferences related to ice cream features and emotional messages. The empirical part of the first phase of the study researches a set of 36 elements, comprising four attributes or categories with nine features each. The attributes were the following:

1. Product features
2. Situation or mood
3. Emotional benefit
4. Brand or other benefit (not emotional).

Each individual evaluated the 36 elements in diverse 60 combinations by means of experimental design (IPED). The sample size of the concept portion of the study comprised 322 respondents drawn from the opt-in MJI Web panel.

The substantial amount of data afforded a three-segment solution for a pattern-based latent segments discovery. In addition, the large base of 322 respondents was divided into many different subgroups, based upon the self-profiling classification questionnaire administered after the evaluation.

The second part of the empirical research explored sensory evaluation of the 22 commercially available variations of vanilla ice cream with 100 pre-recruited respondents. The objective of the study was to understand the drivers of liking, which is a typical objective for studies utilized on the initial stages of NPD.

STUDY III consists of three separate projects (different rating questions for diverse end uses of the product) with 439, 313 and 611 respondents correspondingly randomly drawn from the MJI Web panel that were incentivized by a sweepstake offer.

The concepts were presented one at a time to the respondents for rating the product concepts on an anchored 9-point rating scale, whose language varied with the specific project. The rating question was either 'How interested are you in this cookie?' (Project 1), 'How likely are you to eat this cookie as a snack?' (Project 2) or 'How likely are you to serve this cookie to guests?' (Project 3).

Table 4 contains the summary of the samples for the projects.

Table 4. Sample size and methodologies of the studies. (Source: created by the author).

Study	Dataset	Sample	Methodology
I	Dataset 1	38	Conjoint Analysis (Ideamap.NET SaaS, Web)
	Dataset 2	439	Conjoint Analysis (Ideamap.NET SaaS, Web)
II	Dataset 1	322	Conjoint Analysis (Ideamap.NET SaaS, Web)
	Dataset 2	100	Sensory Questionnaire (central location, NY)
III	Dataset 1	439	Conjoint Analysis (Ideamap.NET SaaS, Web)
	Dataset 2	313	Conjoint Analysis (Ideamap.NET SaaS, Web)
	Dataset 3	611	Conjoint Analysis (Ideamap.NET SaaS, Web)

The setup, data collection and analyses of the results followed the steps of the RDE process described earlier (section 1.2.3).

2. PUBLICATIONS

3. DISCUSSION AND CONCLUSIONS

3.1. Summary and discussions of the findings

The current research has been conducted in the context of the consumer-driven proactive approaches to structured experimentation. The research concentrates on improving the process of obtaining and analyzing consumer preferences of the product concepts through conjoint analysis – one of the major tools in concept development and an integral part of the experimentation-based prototyping on the concept level, increasingly used in NPD. By presenting a series of concepts to a number of respondents and finding out, which are most preferred, conjoint analysis allows the determination of utilities of each of the elements.

The background research described above as well as the materials presented in Studies I–III and other works of the dissertant point to the following development opportunities in consumer-driven experimental design-based approaches to NPD:

- There is a research gap in the field of the approaches to consumer-driven NPD related to detecting and estimating interactions between product features in the context of experimentally designed concepts. Study I and partially Studies II and III as well as other works of the dissertant (Moskowitz, Gofman, Manchaiah, Ma and Katz, 2004; Marketo, Gofman and Moskowitz, 2004; Gofman and Moskowitz, 2006; Gofman, 2008) aim to close this gap.
- Most of the research in the area of NPD concentrates on the industrial rather than food related areas where the majority of the product development happens in mature categories. The traditional limitations of the resources allocated for NPD in mature product categories make this field present special academic and practical interests. The dissertation mainly concentrates on this area, with all the empirical projects and the focus of the proposed methodologies aiming to improve the process (Study III and partially Studies II and I). Other works of the dissertant (Moskowitz, Gofman, Beckley and Ashman, 2006; Gofman, Moskowitz and Mets, 2009b) further develop the research.
- There is an unfulfilled need for low-cost, effective and reliable testing of new product features on the concept level (Dahan and Srinivasan, 2000) which should be systematic and disciplined (Trott, 2008). The research in this dissertation and other works of the dissertant (Moskowitz and Gofman, 2007; Gofman, Moskowitz and Mets, 2009a) as well as partially Studies I – III introduce a formalized structured approach applicable to NPD, Rule Developing Experimentation.
- Conjoint analysis, an experimental design-based approach, is frequently used to understand the consumer preferences, particularly in product development. The existing conjoint analysis approaches are able to test only a limited number of pre-selected combinations of elements for possible interactions between them. There are no reliable and actionable

methods to detect any and all such interactions. Study I addresses the problem of detecting all explicit interactions by introducing an approach based on isomorphic permuted experimental designs. In addition, the methodology introduces another way of dealing with interactions – implicit interactions. The latter facilitates 'what-if' analysis for a developer allowing to see the performance of features of the researched product as a function of other elements.

- A drawback of the current methodologies is the relative nature of the part-worth utility values of the elements that prevents the comparison, knowledge accumulation and reuse. Ability to accumulate this type of information could improve the NPD process, particularly in the mature food categories. The research in the following sections on isomorphic permuted experimental designs along with the materials of Studies I and II address this shortcoming of the existing methodologies by facilitating estimations of absolute rather than relative values of part-worth utilities in conjoint analysis.
- Some businesses and societies have a misperception that there is not much place for innovation in mature product categories, specifically food products, and the efforts should be concentrated only on NPD in emerging areas. Studies I–III demonstrate on the empirical cases that the notion is incorrect and there is always a place for innovation, even in mature food categories which are especially difficult for the developers. Study III further develops combinatorial innovation process (Varian, 2003) by proposing a structured approach to studying the category. Study II introduces an approach for accumulation of information that could be used in NPD for mature product categories.

The dissertation uses these opportunities to research the issues related to consumer-driven experimental design-based approaches to new product development.

Corporations frequently rely on the instincts of designers to develop new products. Schroeder (2005) suggests that successful product design frequently depends on a genius of a designer (developer) who just happens to know what consumer likes. Studies I-III show the value of structured innovation process based on consumer research thus confronting the views of Schroeder (the summary of the main finding are listed in Table 5). The dissertation unambiguously sides with a large school of researchers that believes in the power of consumer preferences knowledge in product development (von Hippel, 1986, 1988, 2005; Moskowitz et al., 2005; Malhotra, and Segars, 2001) as well as in consumer-driven systematic and disciplined approached to NPD (Trott, 2008). Findings of Study I and III demonstrate on empirical cases the wealth of important for product developer information that could be available to a developer empowered by innovative processes of obtaining consumer preferences knowledge.

Table 5. Summary of the major findings

Study	Objective	Sample	Findings
I	Research latent interactions between the elements in the conjoint analyses (explicit and implicit).	*Dataset I:* 38 *Dataset II:* 439	1. Isomorphic Permuted Experimental Designs (IPEDs) create a wide array of experimentally designed concepts that includes all possible evenly distributed pairwise combinations between the elements thus allowing for statistical testing of any and all such interactions and imputation of their magnitude. 2. In most cases, only a small fraction of explicit interactions is significant. 3. Implicit interactions analysis for product development facilitates 'what-if' scenarios of the effect of features substitutions due to technological or economical constraints or preferences on the predicted consumer preferences. 4. Significant explicit interactions can add as many as 10% to 30% to conditional probability of the consumers' purchase intent or can subtract a similar amount if the combination is suppressive.
II	Research and elaborate methodologies aiming to facilitate NPD for mature product categories through structured research, archiving and reusing of the knowledge in a product category utilizing RDE.	*Dataset I:* 322 *Dataset II:* 100	1. It is necessary to experiment and test multiple systematically varied concepts to identify patterns of elements that drive consumer preferences. 2. The results suggest that dividing the consumers into latent pattern-based segments, facilitated by the IPEDs, leads to more targeted products with higher predicted consumer preferences compared to the average models of demographic subgroup analysis. 3. The research of the pattern-based segmentation done across 30 products demonstrates that understanding consumer preferences though pattern-based segmentation produces the insights leading to more targeted and effective NPD. 4. The proposed two-part methodology (conceptual and sensory) provides structured information to product developers. It facilitates the archiving of the current knowledge for sharing and reuse in NPD.

Study	Objective	Sample	Findings
III	Research and elaborate the process of innovating product features in categories typically considered to be mature.	*Dataset I:* 439 *Dataset II:* 313 *Dataset III:* 611	1. The proposed process in the form of combinatorics-led systematized recombination of product features in NPD based on the information afforded by RDE facilitates innovation in mature food categories. 2. The actual identification of innovation opportunities emerges from the segmentation of respondents into pattern-based latent segments of individuals. 3. Inclusion of the features that act synergistically (have positive explicit interactions) increase the conditional probability of consumers being interested in the new cookies by between 13% and 20%. 4. The introduced methodology creates a foundation for an extension based on the emerging applications for automatic collection and classification of the input materials with 'web spiders' and content analysis. This in turn creates a foundation for a systematic RDE-facilitated process for semi-automatic consumer preferences collection.

The findings of Study I confirmed the research of Green and Devita (1975) and Carmone, Green (1981), Ping (1995), and Evgeniou et al. (2002) that besides the individual contribution of the elements, some specific pair-wise combinations might have an additional utility score on consumer liking or purchase intent, which are called interactions. While some researchers describe simple methods for conjoint analysis that ignore interactions on the premise that the interactions are contained within by virtue to mixing of elements yet not estimable (Chrzan and Orme, 2000), the findings of the Studies I and III prove that significant explicit interactions can add as many as 10% to 30% to conditional probability of the consumers' purchase intent or can subtract a similar amount if the combination is suppressive

A foundation of conjoint analysis is an experimental design – a statistical plan that lays out the combinations of the concept elements. Traditional approaches, as described in Atkinson and Bailey (2001), and Hunter and Hunter (2005), apply an experimental design to a set of variables only once creating a single design for all respondents (sometimes randomized). This leads to bias in results as some strong element could influence the ratings due to insufficient variation in combinations. Moskowitz (1994) suggested another approach that permutes the original design and thus creates a wider distributed set of concepts thus improving the quality of the process.

The findings of the Study I confirmed the advantages of that approach in reducing a possible skewness in the results of conjoint analysis. This is achieved by increasing the number of distinct concepts. The dissertation further developed the approach resulting in a methodology suggested to be called Isomorphic Permuted Experimental Designs (IPEDs). IPEDs create a wide and diverse array of experimentally designed concepts that includes all possible evenly distributed pairwise combinations between the elements thus allowing for statistical testing of any and all such interactions and imputation of their magnitude, thus overcoming a limitation of the existing approaches – insufficient variation of combinations. The Study I showed that such permuted designs aid in reducing the bias created by limited number of tested concepts utilized in alternative approaches to conjoint analysis (Atkinson and Bailey, 2001; Hunter and Hunter, 2005). The findings of the Studies I-III suggest that dividing the consumers into latent pattern-based segments, facilitated by the IPEDs, leads to more targeted products with higher predicted consumer preferences compared to the average models of demographic subgroup analysis, thus confirming the research of Moskowitz et al. (2005).

One school of the researchers specializing in conjoint analyses referenced in Melles, Laumann, and Holling (2000) utilizes complete concepts approach in which all features of the product are included in every concept. The limitations of this approach to experimental design are severe interlinked statistical problems in the analytic phase that could lead to biased results, collinearity, inability to estimate the basic level of interest and absolute utility values of the individual elements. The dissertation follows an alternative approach described in Moskowitz et al. (2005) that utilizes incomplete concepts approach allowing for absence of some categories in selected concepts. IPEDs methodology is based on such approach. The findings of the empirical studies I-III confirm the advantages of the methodology. An advantage of incomplete concepts approach described in Studies II and III allow for data comparison and accumulation leading to a reusable data store of product features for product developers to jump-start innovation process as well as estimation of the true basic level of interest and individual utilities because it eliminates collinearity problem of the existing methods.

Galizzi and Venturini (1996) argues that low success rate of new product launches in food industry is partially caused by persistent corporate misperception that eating preferences change slowly and that consumer avers to excessively novel food. Conversely, Prescott et al. (2002) points that consumers' food consumption preferences and behavior changes over time. The findings of the Study II in the present dissertation along with other longitudinal research of the dissertant confirm the findings of Prescott et al. (2002). In addition, the research confirmed the conclusions made by Grunert et al. (1996), Moskowitz et al. (2005) and Rabino et al. (2007) that consumers discernibly differ in their food preferences (particularly, findings of Study II on pattern-based segmentation). The implication of these findings is that corporations are impelled to more proactively innovate their products to be able to compete, thus further corroborating the views of Grunert et al. (1996) and Trail and Grunert (1997). This is particularly important in commoditized and mature industries such as food products.

In many cases, as demonstrated in Leonard (2002), it is difficult for consumers to articulate their needs, wishes and motivations regarding their purchasing and other preference based decisions. An easier and more natural task for the consumers is to make a choice between several presented options in the form of concepts. Unlike direct questioning, RDE presents consumers with sets of experimentally designed concepts based on isomorphic permuted designs and solicits their ratings. The research has confirmed the findings of Kantowitz et al. (2008) that this task is much easier for the respondents as it involves a simple choice between the options resembling routine purchase decisions with the following conjoint analysis-based process of statistically deducing the individual utilities of the elements.

Study I researches latent explicit and implicit interactions between the elements in the conjoint analyses. The proposed methodology discovers any/all explicit interaction between the elements facilitated by the isomorphic permuted experimental designs. In most cases, only a small fraction of interactions is significant. For example, in the orange beverage dataset (Study I), out of the 216 pairs of elements in the orange beverage study only 5% of the explicit interactions were significant. It is not necessary to work with synergistic combinations, but rather the synergism is an extra benefit that should be taken advantage of if possible. In contrast, it is important to avoid the suppressive combinations.

Using the scenario approach (implicit interactions) could be of particular significance addressing a key goal to identify the combination of features that go together. During the NPD process, the developer can use this approach to compare the effect of substituting some features of the product with technologically or economically more viable alternatives on predicted consumer preferences. The utilities of some elements are 'directed' by the contextual presence of other pivotal elements thus creating an opportunity to analyze the problem with a 'what-if' approach.

The first dataset of the Study I analyses the consumer response to different sweetener types, to determine whether the sweetener name can affect acceptance. The variables in this study were primarily emotional in nature dealing with marketing issues and exemplifying the utilization of the implicit interactions in NPD process. This application of the approach to evaluating the reaction of the consumers to various features or marketing messages as a function of brand or other pivotal categories is further researched in other works of the dissertant (Gofman et al., 2006; Moskowitz and Gofman, 2005; Moskowitz, Gofman, Beckley, and Ewald, 2005).

Study II researches an approach to increase consumer knowledge utilization in the NPD process of food corporations through creation a database of product features in mature food categories. The proposed two phases (conceptual and sensory) during the database creation provide structured information to product developers and archive current knowledge for sharing and reuse. The first phase of the database comprises systematic analysis of product concepts, which contain elements dealing with both features and emotions. This phase builds a knowledge base about product features, along with responses to emotional elements and brands aiming to develop a model showing how different concept elements (features) drive consumer interest / purchase intent.

The second phase conducts a sensory analysis of the competitive frame of products. This phase identifies expected ranges of product-sensory features, levels of acceptance of typical products, relations between liking and sensory attributes and segmentation of sensory preferences. Together, the information collected in the two phases provides a guide to product developers facilitating archiving and reuse of the current knowledge. The Study suggests the inclusion of the following information in the knowledge database while demonstrating the approach on another example of a mature food category, ice cream:

1. *Concepts* (product descriptions, brands and emotions). The study argues that instead of limiting the information available to product developers to only product features, as the current practice uses it, any type of information, which has a concrete descriptive nature or an evocative disposition such as brand name or emotion, helps the product developer.
2. *Products* (sensory analysis). The current practices in sensory analysis usually rely on expert evaluation rather than consumer-based due to a perception that consumers cannot properly describe sensory attributes and should be involved only to solicit their overall liking. Study II argues that the database ought to include consumer data, with expert-panel data

complementing the consumer data if these are available, as there is more consumer data available than expert-panel data, and it is practically easier to acquire.

Study III demonstrates the RDE approach in the context of a mature product category on the example of innovation in product development for cookies. Following the RDE steps, Study III analyses the experimentally designed concepts on three different rating questions pertaining to occasions for cookies usage thus generating three distinct datasets. The research confirmed that it is necessary to experiment and test multiple systematically varied concepts to identify patterns of elements that drive responses. The research also suggests that dividing the consumers into pattern-based latent segments according to the patterns of utilities could generate higher predicted consumer preferences vs. models based on the averages or demographic subgroup analysis.

Study III utilizes the information obtained with RDE to propose a structure for innovation in NPD in mature food categories in the form of systematized recombination of features. It demonstrates the approach on the cookies example. It extends the findings of Study I by analyzing the consumer preferences by varying the respondent's task (rating on three different end uses). The actual identification of innovation opportunities emerges from the segmentation of respondents into like-minded pattern-based latent segments of individuals.

The findings of Studies I, II and III showed that there are latent opportunities for innovation even in mature product categories that could be uncovered with RDE. Of particular interest is the pattern-based latent segmentation of similarly minded consumers based on the patterns of their responses to the experimentally designed concepts taking in account the interactions between the elements.

3.2. Conclusions

The research and studies presented in this dissertation examined the role and methods of detection and estimation of interactions and scenarios between product features in the context of conjoint analysis applications for consumer-driven New Product Development, particularly in mature food categories. A novel approach has been introduced to detect and estimate the magnitude of interactions (synergy and suppression) between the elements of conjoint analysis. Furthermore, the dissertation advanced the research to the level of detecting any and all such interactions. It also researched implicit interactions (scenarios) which help to uncover the variations in consumer preferences under specific constraints (e.g., impact of alternative technologically and economically viable features on the performance of other elements).

The proposed method for interactions detection is based on individual experimental designs in conjoint analysis. The dissertation researched, generalized and extended the approach called permuted isomorphic experimental designs*,* first introduced in Moskowitz (1994) and Moskowitz et al. (1995) to address the issue of a possible skewness of data due to the limited variability in selection of a specific set of combinations of elements in fractional experimental designs. This generalization facilitated the implementation of the IPEDs and interaction detection methodologies in software applications (Idemap® family of products).

Conclusion 1: Conjoint analysis, an experimental design-based approach, is frequently used to understand the consumer preferences in product development. The existing conjoint analysis approaches are able to test only a limited number of pre-selected combinations of elements (features of the products) for possible interactions between them. There is a need for an approach to detect any/all explicit interactions to improve NPD process based on the consumer preferences. An additional way to improve NPD would be an ability to analyze implicit interactions – "what-if" analysis for a developer allowing seeing the performance of features of the researched product as a function of other elements.

Another drawback of the current methodologies is the relative nature of the utilities of the elements in conjoint analyses that prevents the products comparison, knowledge accumulation and reuse. Ability to overcome these limitations could improve the NPD process.

Conclusion 2: Experimental design is a key to discovering interactions between the elements (product features) in conjoint analyses. The approach proposed in this dissertation is based on isomorphic permuted experimental designs (IPEDs). IPEDs utilize the underlying experimental design as placeholder for permutations of attributes and elements according to the proposed models. IPEDs methodology allows for the creation of multiple unique (although statistically isomorphic) designs. This methodology facilitates multiple and evenly distributed inclusion of all possible pair-wise combinations of the elements (product features) in conjoint analysis leading to discovery of any and all pair-wise interactions between the elements of conjoint analysis. The approach generates absolute utilities values allowing for comparison and accumulation of data across the projects. In addition, IPEDs make possible pattern-based latent segmentation discovery based on the individual models of utilities, which have absolute values due to the nature of the underlying IPEDs. The approach is generalized for higher order of interactions (between triplets of elements and higher). For example, the empirical parts of the Studies I and III utilize 400 such IPEDs.

Conclusion 3: The proposed methodology utilizing IPEDs uncovers any and all pair-wise interactions between the elements (product features) in the context of conjoint analysis. Empirical results of Study I demonstrates this process. The study analyses the discovered interactions between the features of the orange juice drink (dataset I) and cookies (dataset II). In most researched cases, only a small fraction of interactions is significant: out of the 216 pairs of elements in the orange beverage study and a potential 540 pairs of elements for cookies in Study I, only 5% and 3% respectively were significant. Significant explicit interactions can add as many as 10 to 30 points to purchase intent (approximated to an increase of 10%-30% in the conditional probability of the consumers interested in buying the product) or can subtract a similar amount if the combination is suppressive. The research also demonstrated that implicit interactions analysis (the scenario approach) for product development facilitates 'what-if' scenarios of the effect of features substitutions (e.g., due to technological or economical constraints) on the predicted consumer preferences.

Conclusion 4: The proposed methodological approach to the consumer-driven experimental design-based new product development is a result of the analyses of the hundreds of the empirical projects conducted by the author or with his participation. The dissertation proposes Rule Development Experimentation process consisting of six steps: 1) Preparing Input Materials (e.g., product features and messages); 2) Creating Test Concepts applying IPEDs; 3) Collecting Data With The Consumers (e.g., their purchase intent of the experimentally designed concepts); 4) Analyzing Results / Interactions, including detection of all interactions (explicit and implicit); 5) Identifying Pattern-based Latent Segments; 6) Applying the Generated Rules to Create New Products and Services (rules are quantitative relationship between the features). Steps 1–4 are an adaptation of the steps usually used in conjoint analysis modified based on the proposed improvements. The actual identification of opportunities for innovation in NPD emerges from the segmentation of respondents into like-minded clusters of individuals, with different patterns of utilities with additional fine-tuning based on the discovered interactions between the features.

Study II demonstrates the implementation of the process on the example studying the consumer preferences regarding the features of ice cream.

Conclusion 5: Systematic recombination of R&D-meaningful features (combinatorics or combinatorial innovation) under the guidance of the consumer preferences, researched in the dissertation, is particularly applicable to food product NPD and shown to jump-start the innovation process even in mature categories.

The identification of innovation opportunities emerges from the segmentation of respondents into pattern-based latent segments of individuals. The research demonstrated that targeting segment 2 ('Health Seekers') produces the highest level of predicted consumer preferences.

The introduced methodology creates a theoretical foundation for the possible future extension based on the emerging applications for automatic collection and classification of the input materials with 'web spiders' and content analysis.

Conclusion 6: The results of the dissertation's research are implemented in a system that accumulates and utilizes structured and reusable information of consumer preferences of product features and messages for new product development. Utilizing RDE methodology, the research analyses the foundation of an NPD-oriented database of product features (Study II). The database includes information on the concept and sensory levels. The

dissertation proposes steps towards this knowledge-building process through a two-phase process. The first phase comprises systematic analysis of product concepts, which contains elements dealing both with features and with emotions. The second phase comprises an analysis of the competitive frame of products as an initial input for systematic product development. This phase identifies expected and thus reasonable ranges of product-sensory features, levels of acceptance of typical products, relations between liking and sensory attributes and segmentation of sensory preferences.
The steps are implemented in the empirical part of the Study II. The Study also describes Crave It!™ Foundational Database that systematically researched 30 products. The research identified three pattern-based consumer segments: 'Elaborate', 'Classic' and 'Imaginer'. The elements with high utilities for the 'Classic' segment produce higher predicted consumer preferences than the ones for 'Elaborate' segment. This demonstrates that understanding consumer preferences though pattern-based segmentation produces the insights leading to more targeted NPD.

3.3. Practical value

Experimentation is extremely important for NPD in virtually any field, which is dependent on consumer preferences. The research proposes a way to utilize a systematized and structured experimentation such as RDE to solicit consumer needs and preferences even if the consumers cannot articulate them thus making NPD more targeted and consumer oriented. It results in the corporations' ability to facilitate NPD process based on solid consumer data that is competitive and has projectable results.

The researched approach tests multiple concepts with unique combinations of elements on individual basis thus improving the robustness of the predicted consumer preferences data compared to the traditional approaches of evaluating a limited number of pre-selected concepts or utilizing a single experimental design for every respondent. This results in better products and launches that are more successful. The practical value of the consumer data is further enhanced by IPEDs that facilitate detecting explicit interactions between the features of the products allowing the designers to create products that are more acceptable to the consumers. In addition, implicit interactions afford 'what-if' scenarios for analyzing the impact of substituting features of products on the predicted consumer preferences. This allows a product developer to find a practical compromise between the most economically and technologically acceptable features and consumer preferences.

The nature of the proposed modified conjoint analysis with underlying isomorphic permuted experimental designs facilitates the discovery of the latent consumer needs and wishes that they might not be able to identify themselves or articulate in an actionable way for corporations. Resulting patterns-based segmentation and discovery of any and all interactions lead to the rules (quantitative relationships between the features) that make the products or services more targeted and competitive.

The structured experimentation approach facilitates the ideas formulation during the NPD process thus creating a productive environment for problem solving. The process of preparing the elements for RDE projects stimulates categorization of the issue into different attributes thus facilitating generating more actionable ideas. This also contributes to resolving the problem of the corporate ideation process restrictions during NPD where the most vocal participants or a person with a more senior position could bias the results. RDE removes the judgment phase from the idea generation and delegates it to the consumers thus facilitating freer ideation. The task of the corporate participants becomes not to find 'good' solutions but rather generate 'different' solutions to be evaluated by the consumers. The same applies to the focus groups deeply dependent on the qualifications and objectivity of the moderator.

One of the most important practical benefits of RDE is the facilitation and encouragement of knowledge sharing. The underlying statistical foundation allows for data accumulation, comparison and conversion to actionable knowledge due to absolute values of the utilities and structured nature of RDE. In addition, the generalized approach makes the interpretation of the consumer data understandable across the divisions and ranks of the corporations – from R&D, NPD to marketing and management. The structured approach makes it possible to create general use tools (e.g., Ideamap.NET) that could be utilized for a wide variety of business needs such as but not limited to NPD and message development. The unified methodology and tools in turn make it simpler for corporation to train personnel and disseminate knowledge.

The researched approaches in the form of RDE have been accepted as a practical methodology worldwide for consumer-centric improvements in NPD, message development and other fields. It has been utilized for features, sensory, package and messaging development during NPD at companies such as Coca Cola, Campbell's, McDonalds, Nestle, Pepsi, Kraft, Dunkin' Donuts, Lipton, Tetley, Heineken, Dannon, m&m during early stages of consumer-driven NPD. It has also been utilized (licensed) at Hewlett Packard for NPD, marketing and promotions; licensed by MasterCard for new credit cards offerings; used globally by Unilever, P&G, Microsoft, Ford, American Express, Johnson and Johnson among others.

Consumer-led innovation described by von Hippel (1986, 1988, 2005), in a sense, manifested itself on business-to-business level with RDE. Corporations embraced this new structured approach to NPD and started applying it to other areas as well. HP successfully utilized it, in addition to NPD, for competitive analyses (Macer, 2002). Many new applications of RDE have been suggested or self-applied by the corporations. For example, R. Rex Parris Law Firm (CA) suggested applying RDE to the jury selection process. This has been successfully tested (Perry et al., 2009). Landing page optimization application has been originally requested by Lego based on their experience with the early versions of Ideamap® approach. The research resulting in the new approach for Web page optimization (Gofman, Moskowitz and Mets, 2009a).

3.4. Contributions to the theory

The present research contributes to the theory of conjoint analysis by introducing novel approaches for detecting and estimating interactions. Existing methods either ignore interactions or just test a small set of them on a possibility of interactions. The introduced methods estimating how pairs of communication elements interact with one another to drive consumer interest constitute an important contribution to consumer research. The knowledge of the features synergy in which their net effect is much larger than might be expected from the sum of the individual measurements, is an opportunity to achieve higher consumer acceptance by putting these two synergistic elements together. Conversely, if two elements in combination work suppressively, then early knowledge of the negative effect would suggest the developer avoid using these suppressive combinations in a product.

In addition, the dissertation contributes to the theory of experimental designs by researching, formalizing and further developing the methodology of individual isomorphic experimental designs. Initially suggested by Moskowitz (1994), the methodology has never been fully researched generalized, which hindered its implementation. New conceptual and mathematical models have been introduced.

The present research also contributes to the theory of consumer research in several ways, including expanding experimentation methodologies to NPD, specifically as applicable to consumer-driven NPD in mature food categories. In addition, expanding experimentation approaches (RDE) into consumer-driven NPD for mature food categories contributes to the theory of consumer preferences by establishing procedures and links allowing for the systematizing of knowledge about consumer preferences. Due to the properties of RDE, the knowledge accumulated in separate projects could be aggregated, compared and used for future research and NPD, which was not feasible with unstructured experimentation or traditional experimentation approaches based on the aggregate experimental designs.

The novelty of the approaches has been confirmed by the US patents (Moskowitz and Gofman, 2002; 2005).

3.5. Limitation and suggestions for future research

Studies I-III were limited to small and medium sized projects. The limits of the method were primarily the number of interactions to be sampled. One of the key aspects of the approach here was the ability to combine the data from many respondents into one data file to facilitate testing many elements and many interactions. For example, with eight attributes, each comprising eight elements, there are 64 main effects to be estimated along with 28×64 or 1792 interaction effects. Furthermore, the interaction effects entered the equation only if they added significant predictive power to the variables already in the equation. Thus, the main technical problems confronting the approach for larger datasets were the regression packages, which have lately improved their capacity dramatically.

There are some practical limitations that should be accounted for in the methodology. According to Moskowitz et al. (2005), an average respondent has an attention span of up to 15 minutes and thus could evaluate up to 60–75 concepts (approximately up to 40 elements). For this size of conjoint analysis project, a sample of 200 or more respondents would produce a dataset for statistically significant analyses of pairwise interactions between the elements.

Issues related to interactions that could be further researched in the future:

- Current dissertation researched only the second order of the interactions as the most practical application of the approach. The underlying foundation could be utilized to detect the higher order interactions with the sufficient number of experimental design permutations. The work to extend the approach to the higher degree of interactions needs further research.
- Modifying concept optimization approaches to include pairwise and possibly higher order interactions.
- One of the ongoing issues in the study of interactions is the *'why'*. One might ask why certain combinations do unusually well or unusually poorly. Is this simply a statistical aberration? Are the interactions repeatable? Those questions cannot be answered as yet and might be researched in the future.

The approach to combinatorial innovation researched in Study III could be extended in the future with the virtual automation of the methodology based on emerging options to collect and classify the input materials in an automatic way using evolving applications of 'web spiders' (Chau, Zeng, and Chen, 2001) and content analysis (Krippendorff, 2004). This in turn could serve a foundation for a systematic, semi-automatic, wide-scale RDE process for consumer preferences collection close to real time. The approach should be further researched and developed.

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DICTIONARY OF TERMS
(AS APPLICABLE TO NPD PROCESS)

Adaptive experimentation is a mechanism for ethically applying manipulative experiments in studies of human-dominated ecosystems.

Additive Constant (in conjoint analysis with incomplete concepts) – a baseline interest of respondents in the idea of the product (without any elements present).

Attribute (also variable, silo or category) – in conjoint analysis, a group of related units of decomposition – common elements from which the concepts (conceptual prototypes) are built. Examples of attributes are: "Flavors" (with possible elements such as 'Orange flavored', 'Chocolate flavored', 'Strawberry flavored'); "Fat Content" (with elements such as 'Fat free', 'Low fat'). Only one of the elements from each attribute could be selected into a concept in conjoint analysis. Attributes in conjoint analysis are matched to the respective variables of experimental design (sometimes, the terms are used interchangeably).

Combinatorial Innovation is a process of innovation through re-arranging of the old features in a new way or form. In the context of NPD, combinatorial innovation is a systematic recombination of R&D-meaningful features.

Complete Concepts Approach – every attribute is represented in each of the concepts. Traditional conjoint analysis approaches are based on the complete concepts resulting in estimation of relative values of utilities that cannot be compared across the attributes and projects.

Concept (prototypes, conceptual prototypes) – a testing unit representing a combination of elements according to a unit of experimental design. It represents a textual and/or graphical description of a new product idea. In conjoint analysis, concepts are combinations of elements (features or descriptions of a product). A typical concept in conjoint analysis contains between 3 and 7 elements that together describe a product. Respondents evaluate a set of distinct concepts created based on an experimental design and rate each one on one or more rating questions (e.g., purchase intent, interest).

Concept testing is the process of using quantitative and qualitative methods to evaluate consumer response to a *concept* (product idea) prior to the introduction of a product to the market.

Conjoint analysis is a statistical technique used in market research to determine how people value different features that make up an individual product or service. Conjoint analysis requires research participants to make a series of concepts (also called trade-offs). Analysis of these trade-offs will reveal the importance of the elements, called utilities.

Consumer Preference is a real or imagined "choice" between alternatives and the possibility of rank ordering of these alternatives, based on happiness, satisfaction, gratification, enjoyment, or utility they provide.

Consumer segmentation refers to the division of respondents by one or another set of criteria such that respondents in one segment are more similar on a set of criterion attributes.

Element – a unit of decomposition in conjoint analysis. Could be a feature, message or other unit of experimentation with consumers that are combined into concepts. They are concise descriptive sentences or other media creating individual elements of the products grouped into attributes of similar features. Examples of the elements: "Comes in a sealed metal can"; "0 % APR for the first six month"; "Low-fat". Elements in conjoint analysis are matched to the levels of the respective experimental design (sometimes, the terms are used interchangeably).

Experimental design – a statistical plan that lays out the combinations of the concept elements. It is a foundation of conjoint analysis, as well as several other experimentation-based approaches.

Experimentation (structured and unstructured) is the act of subjecting to experimental test in order to determine how well something works (e.g., concept or element). *Structured* experimentation utilizes design of experiments approach, while *unstructured* experimentation is mostly random and based on predilections.

Experimental Unit – a single line of an experimental design.

Interactions occur when the combined effect of two attributes is different from the sum of their two main effect utilities. *Explicit interactions* are pairs of elements whose combination generates a statistically significant term in a regression equation or in analysis of variance. Explicit Interactions that have combined effect larger than the sum of their two main effect utilities are called *synergisms* (positive interactions). *Suppressions* are interactions, which cause combined effect to be smaller than the sum of their two main effect utilities. *Implicit interactions* – an interaction is viewed as the effect of the conditions on some dependent variable (e.g., the performance of features of the researched product as a function of other elements).

Isomorphic Permuted Experimental Design (IPED) – a type of experimental design created as a result of permutation of the structure of the underlying fractional design to make many different sets of combinations for each individual respondent (model). The permutation of the fractional experimental design creates isomorphic designs that are statistically equivalent to each other.

Level – one of the possible values of a variable in an experimental design. Levels of an experimental design are matched to elements in conjoint analysis (sometimes, used interchangeably)

Optimization (in marketing) – the process of improving the projected consumer perception or the practice of making changes or adjustments to a product/idea/message/package to make it more desirable.

Order (Interaction) – number of elements whose joint effect is investigated. Order is equal to 2 for pair-wise interactions; 3 for triplets of elements, etc.

Partial profile conjoint analysis – in which some (or all) concepts have only a subset of attributes present (as opposed to full profile conjoint analysis in which all attributes are present in every concept).

Pattern-based latent segmentation (RDE segmentation) is a consumer segmentation process of clustering consumers based on the patterns of their individual responses to the concepts regardless of their demographic data.

Respondent – a person who is asked for certain oral or written information during a survey.

Rule Developing Experimentation (RDE) is a systematized solution-oriented business process of experimentation that designs, tests, and modifies alternative ideas, packages, products, or services in a disciplined way using experimental design, so that the developer and marketer discover rules and patterns showing what appeals to the customer, even if the customer can't articulate the need, much less the solution.

Rules of RDE are quantitative relationships between the elements of RDE and consumer perception and directions of how to increase consumer liking (purchase intent) under different scenarios. RDE gives directions regarding what a designer or marketer must do to achieve this goal. It prescribes the most likely combinations of ideas (features, messages) that may be acceptable to the consumer.

Utility score (also utility value, impact or part-worth) – the perceived value of the element; how sensitive consumer perceptions and preferences are to changes in elements. Utilities with *absolute* values could be compared between attributes and across projects. Utilities with *relative* values could be compared only in the context of the attribute they belong to. For example, if an element 'Fat free' from an attribute 'Fat content' has a utility +10 and another element 'Chocolate flavored' from attribute 'Flavors' has a utility +20, in a conjoint analysis with absolute values a researcher could make a conclusion that 'Chocolate flavored' product adds 20% to conditional probability of consumers interest to buy this product, while 'Fat free' adds only 10% to such probability. In a conjoint analysis based on relative values, these utilities could not be directly compared as they have meaning relative to the elements in their own attributes only.

APPENDICES

Appendix A. An example of permuted individual experimental designs.

Table A-1. Examples of two permuted individual experimental designs (two respondents) utilized in Study III with ratings assigned by the respondents to each individual concept. The permuted designs are based on Table A-3. (Source: created by the author).

Unit	Elements																																				Rating
	e_1^1	e_2^1	e_3^1	e_4^1	e_5^1	e_6^1	e_1^2	e_2^2	e_3^2	e_4^2	e_5^2	e_6^2	e_1^3	e_2^3	e_3^3	e_4^3	e_5^3	e_6^3	e_1^4	e_2^4	e_3^4	e_4^4	e_5^4	e_6^4	e_1^5	e_2^5	e_3^5	e_4^5	e_5^5	e_6^5	e_1^6	e_2^6	e_3^6	e_4^6	e_5^6	e_6^6	
Respondent 1																																					
1	0	0	0	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	**9**
2	0	0	0	0	1	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	**9**
3	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	**9**
4	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	0	0	0	**7**
5	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	**9**
6	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	**9**
7	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	**8**
8	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1	0	0	1	0	0	0	**9**
9	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	**5**
10	0	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	0	0	**9**
11	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	**9**
12	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	**8**
13	0	0	0	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	**8**
14	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0	**9**
15	0	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1	0	**9**
16	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1	**9**

Unit	Elements																																			Rating
	e_1^1	e_2^1	e_3^1	e_4^1	e_5^1	e_6^1	e_1^2	e_2^2	e_3^2	e_4^2	e_5^2	e_6^2	e_1^3	e_2^3	e_3^3	e_4^3	e_5^3	e_6^3	e_1^4	e_2^4	e_3^4	e_4^4	e_5^4	e_6^4	e_1^5	e_2^5	e_3^5	e_4^5	e_5^5	e_6^5	e_1^6	e_2^6	e_3^6	e_4^6	e_5^6	e_6^6	
17	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0	**6**
18	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1	**9**
19	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	**9**
20	0	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	**7**
21	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**7**
22	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	**7**
23	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	**9**
24	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0	**9**
25	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	**8**
26	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	**8**
27	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	**9**
28	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	**9**
29	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	1	0	0	**4**
30	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	1	0	0	0	**5**
31	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	**9**
32	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	**9**
33	0	0	0	1	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**9**
34	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	**9**
35	0	0	0	0	0	1	1	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**4**
36	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	**5**
37	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1	**4**
38	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1	0	**3**
39	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	0	0	0	**4**
40	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0	**5**

Unit	e_1^1	e_2^1	e_3^1	e_4^1	e_5^1	e_6^1	e_1^2	e_2^2	e_3^2	e_4^2	e_5^2	e_6^2	e_1^3	e_2^3	e_3^3	e_4^3	e_5^3	e_6^3	e_1^4	e_2^4	e_3^4	e_4^4	e_5^4	e_6^4	e_1^5	e_2^5	e_3^5	e_4^5	e_5^5	e_6^5	e_1^6	e_2^6	e_3^6	e_4^6	e_5^6	e_6^6	Rating
	Elements																																				
41	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	**7**
42	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	**5**
43	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	**4**
44	0	0	0	1	0	0	0	0	0	1	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**3**
45	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0	1	0	**4**
46	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0	1	0	0	0	0	**4**
47	0	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	**8**
48	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	**6**
Respondent 2																																					
1	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	**8**
2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0	**8**
3	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	1	0	0	**7**
4	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	1	0	**9**
5	0	0	0	0	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1	0	0	**6**
6	0	0	0	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	**9**
7	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	**9**
8	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	**9**
9	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	**9**
10	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	**9**
11	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	1	0	0	**8**
12	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	1	0	0	0	0	**9**
13	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	**9**
14	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	1	0	**9**
15	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	0	0	1	0	0	0	0	**8**

Unit	Elements																																				Rating
	e_1^1	e_2^1	e_3^1	e_4^1	e_5^1	e_6^1	e_1^2	e_2^2	e_3^2	e_4^2	e_5^2	e_6^2	e_1^3	e_2^3	e_3^3	e_4^3	e_5^3	e_6^3	e_1^4	e_2^4	e_3^4	e_4^4	e_5^4	e_6^4	e_1^5	e_2^5	e_3^5	e_4^5	e_5^5	e_6^5	e_1^6	e_2^6	e_3^6	e_4^6	e_5^6	e_6^6	
16	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	**8**
17	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	**8**
18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0	0	0	1	0	**8**
19	0	0	1	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	**8**
20	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	**8**
21	0	0	0	0	1	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	**9**
22	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	**9**
23	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1	**8**
24	0	1	0	0	0	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**8**
25	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	**9**
26	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	**8**
27	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	**9**
28	0	0	0	1	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	**9**
29	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1	**8**
30	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	**7**
31	1	0	0	0	0	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	**8**
32	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0	0	**8**
33	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	0	0	0	1	0	0	**8**
34	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	**8**
35	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**7**
36	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	**7**
37	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	0	0	0	**8**
38	0	0	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	**8**
39	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0	**8**

Unit	Elements																																				Rating
	e_1^1	e_2^1	e_3^1	e_4^1	e_5^1	e_6^1	e_1^2	e_2^2	e_3^2	e_4^2	e_5^2	e_6^2	e_1^3	e_2^3	e_3^3	e_4^3	e_5^3	e_6^3	e_1^4	e_2^4	e_3^4	e_4^4	e_5^4	e_6^4	e_1^5	e_2^5	e_3^5	e_4^5	e_5^5	e_6^5	e_1^6	e_2^6	e_3^6	e_4^6	e_5^6	e_6^6	
40	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	**8**
41	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	**9**
42	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	**8**
43	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	1	**8**
44	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	**8**
45	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**9**
46	0	1	0	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	**8**
47	0	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	0	0	0	0	**9**
48	0	0	0	0	1	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	**8**

Appendix B. Example of Implicit Interactions

Table A-2. Example of Implicit Interactions between the brands of the food companies and utilities of messages related to the products. *Source: based on Moskowitz, H., Gofman, A., Beckley, J., and Ewald, J. 2005. Brand Name Anatomy: Experimental Design Assesses the Value of Food Products and Retailer Names. Marketing Research, 17(3):14–19.*

	Kraft Foods (F)	Quaker Oats (F)	Campbell's (F)	Kellogg's (F)	Betty Crocker (F)	Whole Foods (R)	Newman's Own (F)	Wal-Mart (R)	Trader Joe's (R)
Additive constant	*48*	*47*	*46*	*44*	*41*	*37*	*34*	*33*	*31*
As part of a low fat diet, this food may reduce the risk of some types of cancers.	10	-4	4	6	5	**16**	9	**11**	3
Meals that require no preparation. Just heat and eat!	0	-1	0	6	3	**15**	**11**	4	6
Just one serving provides important cancer protective benefits.	-1	5	**11**	1	5	0	9	6	7
Tastes like it was prepared by someone who cared about you.	2	4	0	-2	-1	**13**	8	10	8
Feeling good about feeding your family.	-4	1	6	-2	15	0	3	0	3
Looks great, smells great, tastes delicious.	2	0	2	1	3	3	**11**	-2	2

Appendix C. RDE categorization

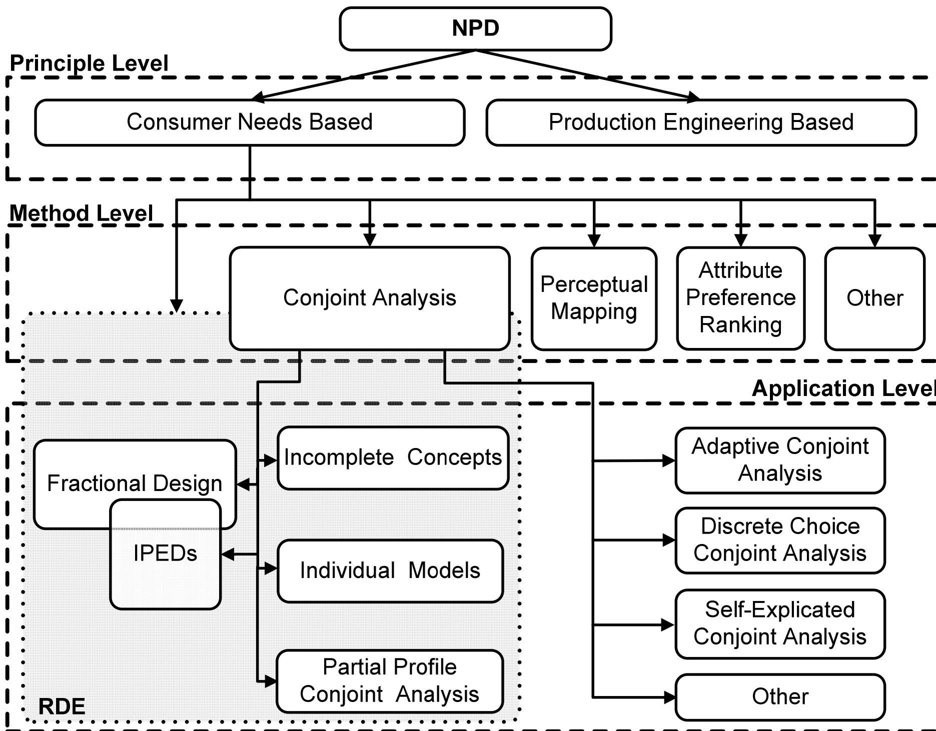


Figure A-1. General categorization of RDE as applicable to NPD. RDE elicits and analyzes consumer preferences of the product prototypes on the concept level. The experimentally designed concepts are tested through partial profile conjoint analysis utilizing a special type of fractional main effects experimental designs (isomorphic permuted experimental designs). RDE incorporates different features from conjoint analysis including modifications introduced by the author. (Source: created by the author).

Appendix D. Example of Implementation of RDE

The process is illustrated on the example of Study III (Dataset 1). First, the input data are collected and formatted into individual elements (Appendix F). Then they are entered into RDE program such as Ideamap.NET (Appendix E has screen captures of the steps in the process in a demo project). As this set of elements comprises six attributes with six elements in each, an appropriate original experimental design for this specific set of elements has been selected (Appendix G). There is a number of different source designs available in statistical literature as well as they could be created with such software packages as SPSS (SPSS, 2007). The permutation module applies the original experimental design to permuted (per each individual respondent) sets of attributes and elements. Appendix A shows two individual permuted designs for Respondents 1 and 2 created utilizing IPEDs approach. The table also includes the ratings assigned by the respondents to each individual concept corresponding to each experimental unit in the source experimental design.

In the next step, respondents evaluate individual sets of concepts corresponding to the individual permuted experimental designs and assign ratings (liking scores) to each concept. The collected data are analyzed with a regression module (elements are independent variables and the rating is a dependent variable) to calculate individual utility scores for each elements per each respondent generating a set of utilities for each element.

The key to understanding the data for product development is the utility scores of the individual elements. To the degree that the elements perform well, the developer will be able to synthesize new and, potentially, breakthrough concepts. To the degree that the concept elements perform only modestly, the concepts will not be breakthrough. Moskowitz et al. (2005) provides the norms for interpreting utility scores and additive constants, listed in Table A-3. The numbers in the table are conditional probability (%) of people being interested in buying the product described. Additive constant in conjoint analysis with incomplete concepts is a baseline interest of respondents in the idea of the product (without any elements present).

For the Dataset 1, 439 respondents rating 60 individually varied concepts generated a set of utilities that were averaged in Table 3 (Study III). Additive constant of 34 means that approximately 34% of the respondents would rate the concept as interesting. This 34% is substantially lower than the 45% of respondents who rate the same concept interesting if the concept is positioned either as one's snack or for serving to guests (Datasets 2 and 3). Positioning therefore appears to have a major effect overall. This means that without end use positioning the elements must do more of the work to convince the respondent to be interested in the concept.

Table A-3. Norms for the additive constant and the utilities (Source: Moskowitz et al., 2005).

Additive constant	*Interpretation*
>60	Respondents are very predisposed to the product
50–60	About half of the respondents are very positive
40–50	Respondents accept the idea
30–40	The elements need to do the work
<30	The product is a commodity and the elements must do the work
Utility score	*Interpretation*
>15	The element performs exceptionally well, breaks through clutter
10–15	The element performs well
5–10	The element breaks through the clutter
0–5	The element is barely effective, if at all
<0	The element actively detracts from acceptance

To create a winning concept for the Total Panel in the Dataset 1 (averaged across all respondents in the dataset), a developer should select the highest scoring elements from each of the attribute.

Estimated consumer interest (total utility score of the concept) could be constructed as a sum of the corresponding additive constant and the utilities of each of the selected elements (Appendix F):

$$C_{t1} = A_1 + B_1 + C_4 + D_3 + E_3 + F_1 = 34 + 8 + 7 + 5 + 11 + 6 + 5 = 76,$$

where $C_{t1}$is the score of the optimized concept for the Total Panel (Dataset 1); $A_1$is element one of attribute A; $B_1$is element one of attribute B, etc. The resulting number (76%) is a conditional probability that the respondents would be interested in the product described by the selected elements.

For comparison, estimated consumer interest for the Dataset 2 is:

$$C_{t2} = A_4 + B_5 + C_5 + D_3 + E_4 + F_1 = 45 + 6 + 5 + 2 + 8 + 3 + 1 = 70,$$

where C_{t2} is the score of the optimized concept for the Total Panel (Dataset 2).

If a developer by mistake selects the lowest scoring elements (e.g., in case when conjoint research has not been conducted and the selection was made based on predilections), the estimated consumer interest would be:

$$C'_{t1} = A_2 + B_2 + C_3 + D_2 + E_2 + F_6 = 34 + 1 + (-1) + 2 + (-9) + 2 + 2 = 31,$$

where C'_{t1} is the score of the concept comprising the lowers scored elements for the Total Panel (Dataset 1). This means that if a developer does not use a structured experimentation and chooses, by chance, the lowest scored elements, the resulting concept would have conditional probability of consumers interested in buying it by about 60% lower than C_{t1} (highest scored).

RDE uses systematically permuted designs, allowing the developer to identify combinations of product features, which exhibit unusually high or unusually low scores relative to what might be expected based on simple, non-interacting effects. The project in study III has six attributes of features, six elements per attribute, 15 pairs of attributes, 36 interactions per pair or a total of 540 interactions which could not be tested by current methods.

In this project only four pairs of elements have strong synergistic effect: E_2+F_2, A_6+E_6, B_3+F_3 and C_6+E_3. For example, the combination of the elements A_6 (*Jumbo size… for when you want a little extra*) and E_6 (*Comes in a crush-proof box… no more broken cookies*) in a model that ignores interactions (a common approach) would produce neutral utilities of +2 for each of the elements with the additive constant +35. This could lead to a conclusion that it is not a very effective combination of features as the conditional probability of respondents being interested in buying this product is less than 40%. A more precise model afforded by RDE with IPEDs checks for all possible interaction between the elements of the project. In this case, the interactions effect is much bigger than utilities values themselves resulting in the total concept score (sum of the constant, individual utilities and interaction effect) of +59. This number suggests that there is a conditional probability of 59% that the respondents would consider buying this product.

In addition, because RDE generates absolute values of the utilities rather than relative, it is possible to compare utilities across the attributes and even some similarly structured projects conducted with the same type of consumers. For example, this allows comparisons of the utilities and additive constants for Datasets 1, 2 and 3 in Study III.

In summary, RDE leads to more reliable results that could be aggregated, stored and reused. The discovered quantitative relationships between the elements include individual contribution of each element to consumer preferences as well as pattern-based latent segmentation, explicit interactions and scenarios (implicit interactions).

Appendix E. Sample Screens of Ideamap.NET RDE Tool (Software-as a-Service Model) (www.ideamap.net)

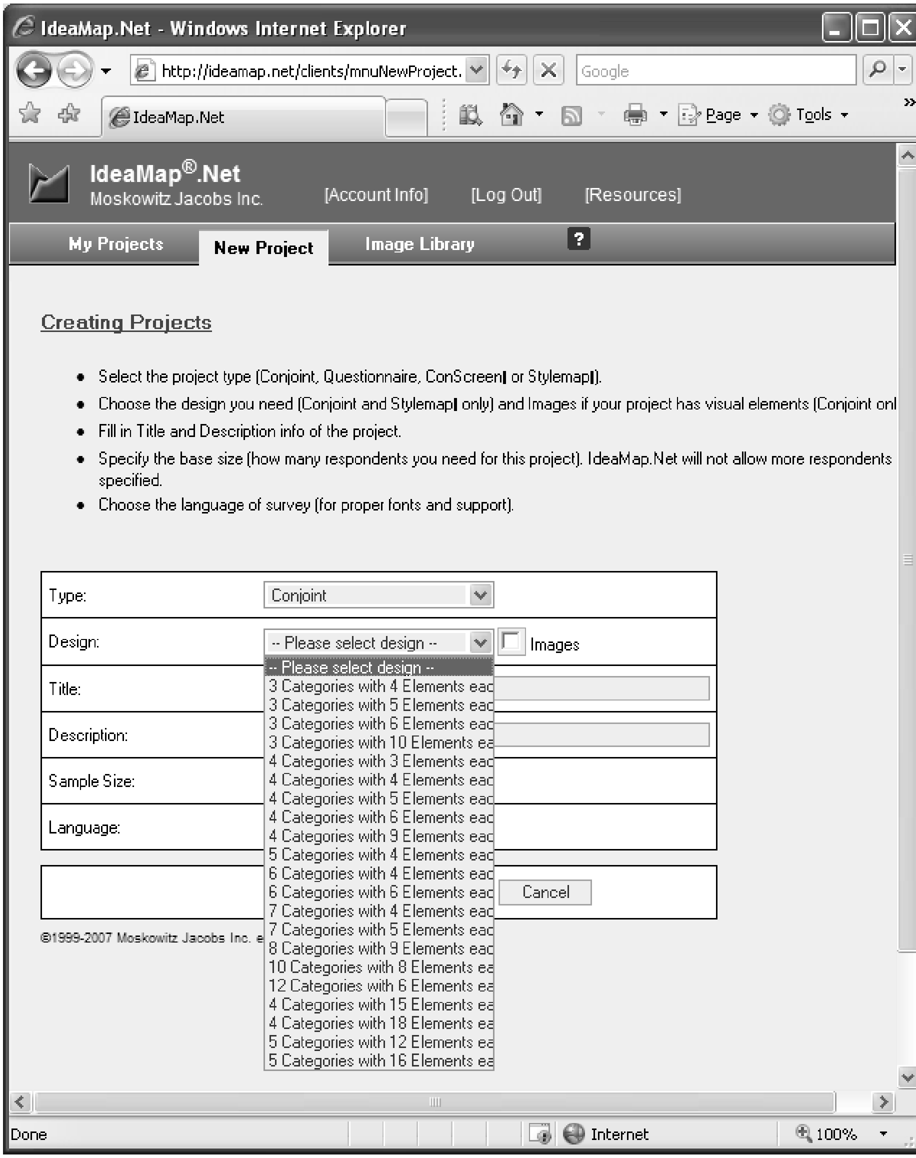


Figure A-2. Screen capture of the project creation step in Ideamap.NET. Drop-down menu shows available designs. (Source: created by the author).

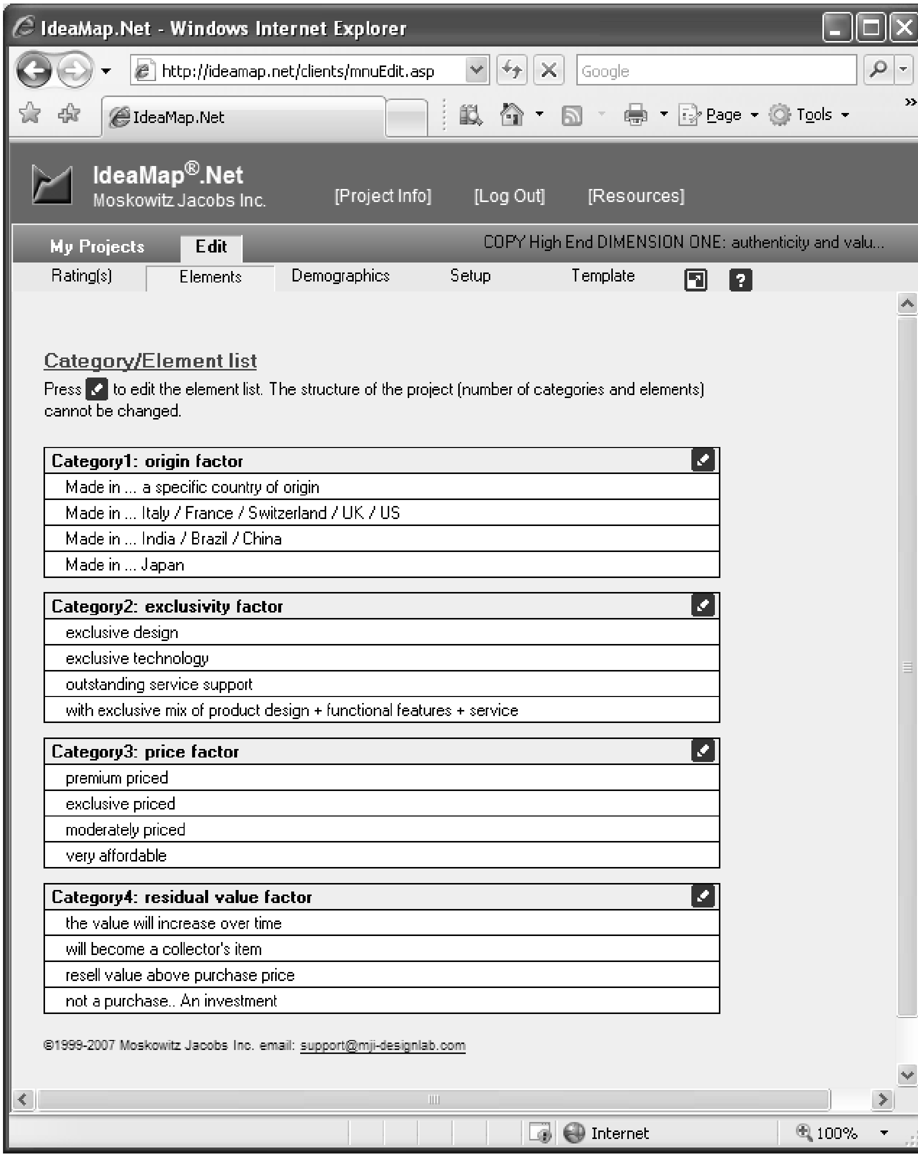
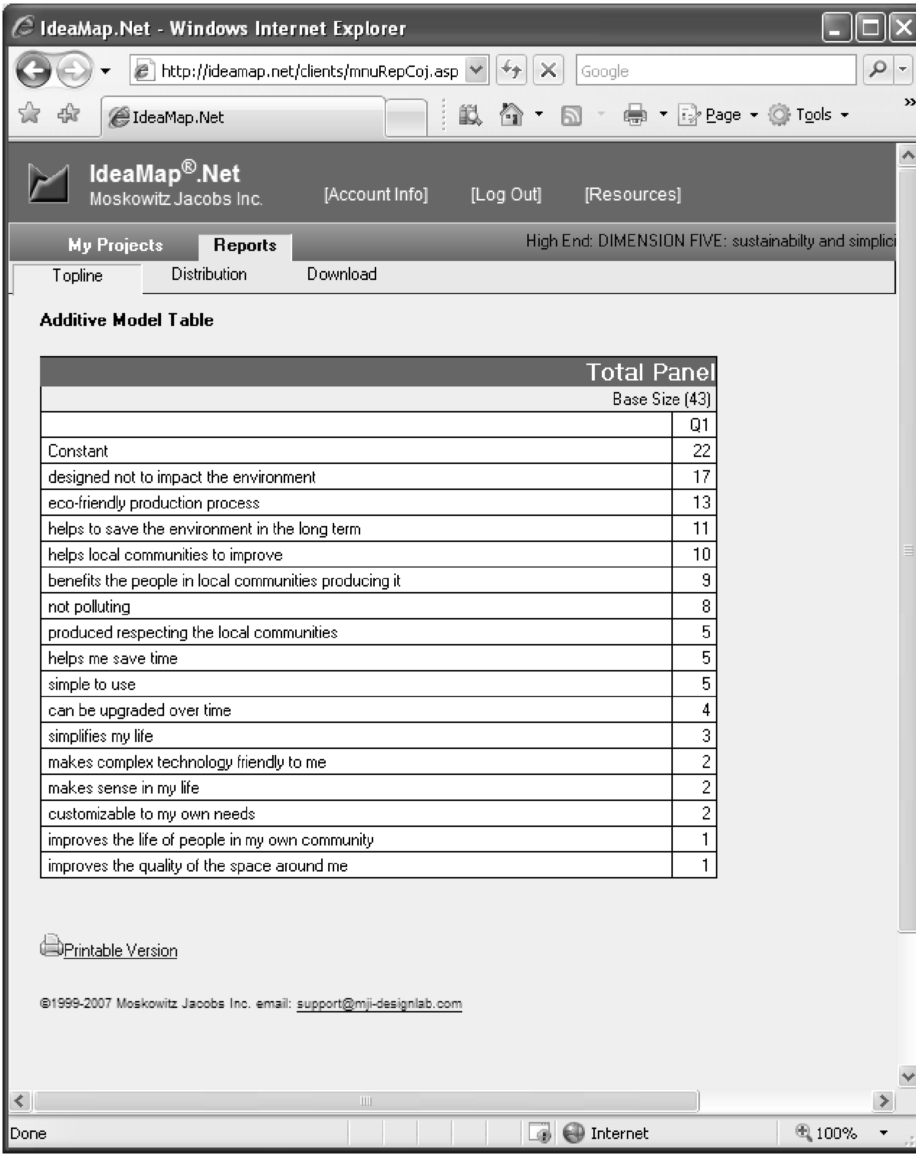


Figure A-3. Screen capture of the elements editing step in Ideamap.NET. (Source: created by the author).

Figure A-4. Screen capture of a concept evaluation page in Ideamap.NET. Every respondent evaluates a set of such concepts. The example shows all four attributes present in the concept. (Source: created by the author).



Total Panel	
	Base Size (43)
	Q1
Constant	22
designed not to impact the environment	17
eco-friendly production process	13
helps to save the environment in the long term	11
helps local communities to improve	10
benefits the people in local communities producing it	9
not polluting	8
produced respecting the local communities	5
helps me save time	5
simple to use	5
can be upgraded over time	4
simplifies my life	3
makes complex technology friendly to me	2
makes sense in my life	2
customizable to my own needs	2
improves the life of people in my own community	1
improves the quality of the space around me	1

Figure A-5. Screen capture of Topline report page in Ideamap.NET. The numbers in the right column represent a conditional probability of consumers assigning top 3 rating scores on the rating question to the element. (Source: created by the author).

Appendix F. Results of Study III (complete set)

Table A-4: The additive constant and the utilities for the total panel, for the three studies. The elements are ranked within the attribute from high to low, based upon performance without position (column labeled Unpos. (un-positioned)). (Source: created by the author).

		Unpos.	Snack	Guest	Range
	Base size	*439*	*313*	*611*	
	Additive constant	*34*	*45*	*46*	*12*
	ATTRIBUTE A – WHAT DOES IT LOOK LIKE, AND FEEL LIKE (APPEARANCE, TEXTURE)?				
A1	Soft and chewy…just like homemade	8	5	3	5
A3	Soft and chunky…for an extra special treat	8	3	4	5
A4	Oversized chunks of dark chocolate to sink your teeth into	7	6	8	2
A6	Jumbo size…for when you want a little extra	5	–1	0	6
A5	Bite size for a quick indulgence	4	0	0	4
A2	Crisp and crunchy…perfect for dunking	1	–3	–2	4
	ATTRIBUTE B – WHAT DOES IT CONTAIN (INGREDIENTS)?				
B1	Real creamery butter for a rich, indulgent taste	7	4	4	3
B5	Made with only the freshest ingredients…eggs, milk, butter	3	5	3	2
B6	Sweetened with natural fructose for a healthy indulgence	2	–3	–2	5
B3	For a healthy source of protein….made with unpasteurized egg whites	1	–3	–3	4
B4	Made with unprocessed whole grain flour…keeping all the goodness in	1	1	–1	2
B2	Made with canola oil which helps lower blood cholesterol levels	–1	3	–1	4
	ATTRIBUTE C – WHAT 'HEALTHFUL FEATURES' DOES IT OFFER?				
C4	0 grams trans fat and cholesterol free…a heart friendly cookie	5	1	–1	6
C5	A high-fiber cookie that boosts your energy level and leaves you feeling full	5	2	–2	7
C6	With no trans fats or preservatives…for a healthy snack you can feel good about giving your kids	5	–1	1	6
C1	Calcium enriched for strong bones	4	–1	1	5
C2	Low carb…when you're counting carbs and looking for a great snack	2	–1	–4	6
C3	With added iron and isoflavones… a cookie that not only tastes good but is good for you	2	–1	–1	3

		Unpos.	Snack	Guest	Range
	ATTRIBUTE D – WHAT FLAVORS DOES IT FEATURE?				
D3	Dark Belgian chocolate, Swiss milk chocolate and bittersweet chocolate…simply irresistible	11	8	11	3
D6	Oatmeal…for old fashioned goodness and packed with nutrition	6	1	5	5
D4	Rich and creamy Peanut butter…for those who love an old favorite	4	3	4	1
D5	Vanilla flavored…a traditional favorite	–2	–2	–3	1
D1	Comes in spicy flavors…cinnamon, nutmeg and allspice	–3	–6	–4	3
D2	Comes in cool, citrus flavors…orange, lemon and lime, perfect for a ladies afternoon tea	–9	–17	–8	9
	ATTRIBUTE E – HOW IS IT PACKAGED OR STORED?				
E3	Comes in resealable bags...take out only what you want	6	1	1	5
E6	Comes in a crush-proof box…no more broken cookies	6	0	0	6
E1	All cookies are individually wrapped for freshness	4	–2	–2	6
E4	Available in variety packs…three of your favorite varieties in one box	4	3	2	2
E2	Comes with a stay fresh inside wrapper…just twist & seal	2	–2	1	4
E5	Available in decorative tins…the perfect gift idea	2	–3	–1	5
	ATTRIBUTE F – WHERE IN THE STORE IS IT FOUND & HOW IS IT MERCHANDISED?				
F1	In the bakery section of your supermarket…always fresh	2	1	3	2
F2	In the frozen foods section of your supermarket…just thaw and serve	1	0	–3	4
F3	In the frozen foods section of the supermarket…bake & serve…hot from the oven	5	–3	0	8
F4	In the refrigerated section of your supermarket…just thaw and serve	1	–3	–2	4
F5	In the refrigerated section of your supermarket…just bake and serve	3	–3	–1	6
F6	Sold in bulk…enough to please a crowd	2	–1	–1	3

Appendix G. Source Experimental Design Utilized in Study III

Table A-5: Original (source) experimental design utilized in Study III for individual permutations. (Source: created by the author).

Unit	Var^1	Var^2	Var^3	Var^4	Var^5	Var^6
1	x_0^1	x_1^2	x_1^3	x_0^4	x_4^5	x_1^6
2	x_1^1	x_6^2	x_0^3	x_0^4	x_0^5	x_4^6
3	x_0^1	x_2^2	x_2^3	x_4^4	x_5^5	x_0^6
4	x_5^1	x_2^2	x_0^3	x_3^4	x_5^5	x_0^6
5	x_3^1	x_0^2	x_3^3	x_4^4	x_0^5	x_1^6
6	x_3^1	x_1^2	x_0^3	x_2^4	x_4^5	x_0^6
7	x_4^1	x_0^2	x_1^3	x_5^4	x_2^5	x_0^6
8	x_2^1	x_0^2	x_3^3	x_0^4	x_2^5	x_0^6
9	x_0^1	x_6^2	x_1^3	x_0^4	x_4^5	x_0^6
10	x_0^1	x_1^2	x_4^3	x_0^4	x_3^5	x_2^6
11	x_0^1	x_5^2	x_1^3	x_4^4	x_6^5	x_0^6
12	x_0^1	x_3^2	x_4^3	x_0^4	x_0^5	x_5^6
13	x_3^1	x_0^2	x_6^3	x_6^4	x_0^5	x_5^6
14	x_2^1	x_4^2	x_0^3	x_1^4	x_0^5	x_2^6
15	x_0^1	x_2^2	x_1^3	x_2^4	x_0^5	x_4^6
16	x_3^1	x_5^2	x_0^3	x_6^4	x_5^5	x_0^6
17	x_2^1	x_0^2	x_6^3	x_0^4	x_0^5	x_5^6
18	x_0^1	x_4^2	x_6^3	x_5^4	x_6^5	x_0^6
19	x_5^1	x_4^2	x_0^3	x_0^4	x_1^5	x_3^6
20	x_5^1	x_0^2	x_5^3	x_6^4	x_0^5	x_3^6
21	x_4^1	x_0^2	x_5^3	x_0^4	x_3^5	x_5^6
22	x_2^1	x_3^2	x_0^3	x_6^4	x_0^5	x_6^6
23	x_1^1	x_0^2	x_2^3	x_5^4	x_6^5	x_0^6
24	x_6^1	x_0^2	x_4^3	x_0^4	x_5^5	x_2^6

Unit	Var^1	Var^2	Var^3	Var^4	Var^5	Var^6
25	x_0^1	x_3^2	x_2^3	x_3^4	x_1^5	x_0^6
26	x_0^1	x_5^2	x_4^3	x_0^4	x_0^5	x_4^6
27	x_6^1	x_1^2	x_0^3	x_3^4	x_1^5	x_0^6
28	x_2^1	x_0^2	x_0^3	x_1^4	x_0^5	x_2^6
29	x_6^1	x_6^2	x_0^3	x_3^4	x_0^5	x_4^6
30	x_0^1	x_4^2	x_4^3	x_0^4	x_3^5	x_6^6
31	x_4^1	x_5^2	x_0^3	x_0^4	x_6^5	x_3^6
32	x_0^1	x_2^2	x_3^3	x_0^4	x_0^5	x_1^6
33	x_6^1	x_0^2	x_2^3	x_1^4	x_4^5	x_0^6
34	x_6^1	x_0^2	x_0^3	x_2^4	x_2^5	x_3^6
35	x_4^1	x_3^2	x_0^3	x_0^4	x_0^5	x_5^6
36	x_5^1	x_0^2	x_6^3	x_0^4	x_3^5	x_6^6
37	x_0^1	x_4^2	x_5^3	x_4^4	x_3^5	x_0^6
38	x_0^1	x_5^2	x_6^3	x_2^4	x_0^5	x_1^6
39	x_0^1	x_6^2	x_2^3	x_1^4	x_5^5	x_0^6
40	x_1^1	x_0^2	x_0^3	x_3^4	x_0^5	x_2^6
41	x_1^1	x_0^2	x_5^3	x_0^4	x_1^5	x_6^6
42	x_0^1	x_6^2	x_0^3	x_4^4	x_0^5	x_6^6
43	x_0^1	x_3^2	x_3^3	x_1^4	x_2^5	x_0^6
44	x_3^1	x_0^2	x_3^3	x_5^4	x_1^5	x_0^6
45	x_4^1	x_2^2	x_0^3	x_2^4	x_6^5	x_0^6
46	x_1^1	x_0^2	x_5^3	x_0^4	x_4^5	x_3^6
47	x_5^1	x_0^2	x_0^3	x_6^4	x_2^5	x_4^6
48	x_0^1	x_1^2	x_0^3	x_5^4	x_0^5	x_1^6

SUMMARY IN ESTONIAN

Eelistusanalüüsi täiustatud metoodika rakendamine eksperimendipõhises tootearenduses küpsusfaasis toidukaupade näitel

TÖÖ AKTUAALSUS JA VALDKONNA ÜLEVAADE[2]

Innovatsioon on saanud üheks peamiseks äri edukust määravaks jõuks. Viimaste aastakümnete jooksul on tarbijaid üha enam kaasatud innovatsiooniprotsessi. Von Hippeli (1986, 1988, 2005) ning von Hippeli ja Katzi (2002) uuringutes juhitakse tähelepanu selle kaasatuse tähtsusele innovatsiooniprotsessis, iseäranis tootearenduses: tarbija ja turu tundmine võimaldab parandada protsessi tulemuslikkust (Berghman, Matthyssens ja Vandenbempt, 2006; Gold, Malhotra ja Segars, 2001; Möller, 2006) ja efektiivsust (Inkpen ja Dinur, 1998; Sanchez ja Mahoney, 1996).

Uue toote arendus (UTA või lihtsalt: *tootearendus)* ning vastavad äriprotsessid omandavad üha kasvavat tähtsust teadmuspõhises majanduses. Paljud uurijad ja kasvav hulk ettevõtteid on jõudnud arusaamisele UTA tähtsusest ettevõtte konkurentsieeliste loomisel (Hunt ja Morgan 1995). Kiire, efektiivne ja reeglipärane toodete uuendamine on otsustava tähtsusega kaasaegse ettevõtte majandusedus, sest see võimaldab firmal hõivata eelispositsiooni turul, arvavad Wood ja Otto (2006).

Uute toodete turuletoomine on muutunud ärikasvu mootoriks (Riquelme, 2001; Sherman, Berkowitz ja Souder, 2005; Thomke, 1998, 2001, 2003). Paraku, suur osa uue toote lansseerimistest ebaõnnestub. Flavini (2008) põhjal on enamikus valdkondades ebaõnnestumise määr 50 ja 75 % vahel. Valdkonnaspetsiifiliselt, edumäär toidutööstuses on madalam kui tööstussektoris üldiselt. Goldman (2005) väidab, et enamik uue toidukauba turuletoomisi on konkurendi kopeerimine, see on viinud ebaõnnestumise määra 72–88 %-ni (vaata samuti: Buisson, 1995; Rudolph, 1995; Lord, 1999).

Costa ja Jongen (2006) põhjal on radikaalselt uued tooted Euroopa toiduturul harv nähtus (ainult 2,2 % tootelansseeringute koguarvust), ehkki Lordi (1999) ja Rudolphi (1995) varem tehtud uuringud annavad selleks väärtuseks 7 ja 25 protsendi vahemiku 1990-nendate keskel ja teisel poolel.

Viimaste kümnendite sotsiaalmajanduslik areng Lääne ühiskonnas on toidutööstuses käivitanud nihke tootmisorientatsioonilt turuorientatsioonile (Grunert et al., 1996; Meulenberg ja Viaene, 1998; Traill ja Meulenberg, 2002), selle tulemusena on alanenud toote kättesaadavuse ja hinna tähtsus toidukaupade

[2] Spetsiifiliste mõistete selgitus on toodud k.o. kokkuvõtte lõpus

ostmisel ja kasvanud on *tarbija valikuvõimaluse* kui kriteeriumi suhteline tähtsus (Meulenberg ja Viaene, 1998; van Trijp ja Steenkamp, 1998).

Galizzi ja Venturini (1996) väidavad, et toidutööstuse innovatsiooni põhitakistuseks on jätkuvalt toitumiseelistuste aeglane muutus ja tarbijate vastuseis liigselt uudsetele toidukaupadele. Paljud tunnused viitavad sellele, et toitumisharjumused on suhteliselt muutumatud (Prescott et al, 2002). Kuid samas, tarbijaid eristab nende toidueelistus, nagu on tõestanud Grunert et al (1996) ja Rabino et al (2007). Selle tähelepaneku põhjal Grunert et al. (1996) ning Trail ja Grunert (1997) järeldavad, et innovatsioonist globaalsetel toiduturgudel on saamas ennemini vajadus kui lihtsalt võimalus.

Garcia et al (2007) märgib, et uute toidukaupade kõrge ebaõnnestumismäär on tingitud kasutatavast tootearendusprotsessist. Kuigi on teada palju tootearendusprotsessi edu ja ebaedu mõjureid, põhineb nendest arusaamine ennemini muu tööstuse kui toidutööstuse uuringutel (Kärkkäinen, Piippo ja Tuominen, 2001; Stewart-Knox ja Mitchell, 2003). Fernandez ja Gomez (2005) leiavad, et UTA protsessi keerukuse kasvu toidutööstuses on teravalt mõjutanud turu iseloom, kuna toidukaupade turg on küpsuses ning selle kogumaht ja väärtus on pigem püsiv kui kasvav. Harris (2002) märgib, et osa toidukaupade sortimendi ulatuslik mitmekesistamine on paljude toodete turu viinud küllastussse ning ajanud tarbijad segadusse.

Eelmärgitud tootelansseeringute edukuse suurt varieeruvust 2.2...25% Euroopas erinevate autorite andmetel (Costa ja Jongen, 2006; Lord, 1999; Rudolph, 1995) võib selgitada nende uuringute vahelise ligi 10-aastase intervalliga. Euroopa toidu- ja joogitööstust iseloomustab teistest majandussektoritest suurem konservatiivsus ning madalam teadusuuringute ja arendustöö (T&A) investeeringute tase. Ligikaudu 77-l protsendil kõikidest tootelansseeringutest puudub uudsus täielikult või on selle tase vaevumägatav (Avermaete et al., 2004). Taoline lähenemine innovatsioonile, mis hoiab T&A kulutused madalad ning lubab ainult tehnoloogilisi pisiriske, ei võimalda tuua turule suhteliselt suurt arvu erinevaid tooteid lühiajalisel perioodil.

Garcia et al (2007) ja Beckley (2007) arvavad, et innovatiivsetel toiduainete ettevõtetel on jätkuvalt turuvõimalusi, kui nad vastavad tarbijate vajaduste ja toiduga seotud elustiili muutustele. Uute toodete arendamine ja innovatiivsus nõuavad ettevõtetelt sügavat arusaamist oma tarbijast, turust ja keskkonnast, kus toimitakse, kuid kõige tähtsam on selle teadmise efektiivne rakendamine tarbija ootustele vastavates toodetes. See tekitab vajaduse rakendada efektiivset, struktureeritud ja tarbija-orientatsiooniga UTA protsessi (Beckley, 2007).

Üheks sellise eesmärgi saavutamise teeks on *eksperimenteerimine*, kasutades tarbija-keskset eksperimenteerimismetoodikat nagu on välja toonud Thomke (2001, 2003), Kahn, Barczak ja Moss (2006). Kasutatakse kahte võistlevat lähenemisviisi eksperimenteerimisele: *struktureerimata* ja *struktureeritud*. Osa tarbijaeelistusi kasutavatest eksperimenteerimismeetoditest põhinevad kas juhuslikul või subjektiivsel eksperimenteerimisobjekti valikul või on kauakestvad ja keerukad (nagu adaptiivne eksperimenteerimine, Sasena et al, 2005) ning ei loo kasutatavaid tegevusjuhiseid. Ziman (2000) ja Trott (2008) märgivad, et vaatamata arenevate eksperimenteerimismeetodite selgetele eelistele, paljud ettevõtted kasutavad tootearenduses sageli struktureerimata katsetusi. Neid tähelepanekuid kinnitavad Wind ja Mahajan (2001) ning Belson (2003), nad analüüsivad äriprotsesse Seiko ja Sony korporatsioonides, mis töötavad iga-aastaseks testimiseks välja sadu toote prototüüpe. See laiaulatuslik peamiselt struktureerimata katsetamine on mõeldav, nagu arvavad Balasubramanian, Krishnan ja Sawhney (2001), prototüüpimise kahaneva maksumuse tõttu, mis lubab paljukordset prototüüpimist nõudmata tingimata süsteemset katsetamist.

Samal ajal, on palju tõendusmaterjali, et struktureeritud ja süsteemne eksperimenteerimine on palju efektiivsem ja eesmärgipärasem (Balasubramanian, Krishnan ja Sawhney, 2001). Dickinsoni ja Wilby (1997) läbiviidud uuring näitab, et paljudel juhtudel, nagu tootesarja laiendamine, efektiivsed tootekontseptsiooni testid ei nõua isegi tootekatseid. Vastupidi, see tõstab esile tarbijaeelistustel põhineva tootekontseptsiooni tasemel testimise kasulikkuse (Moskowitz, Porretta ja Silcher, 2005).

Haagedoorn (1996), Nooteboom (1999) ja Soumodip (2007) määratlevad innovatsiooni kui uue loomist või vana ümberkorraldamist uuel viisil *kombinatoorse innovatsioonina* (Fagerberg, 2006; Langlois, 2004). Üheks põhiliseks protsessiks kombinatoorses innovatsioonis on kliendieelistustest tingitud (Rabino et al, 2007) ja ennemini eksperimendi disainil kui juhulikul valikul põhinevate oluliste tooteomaduste süsteemne rekombineerimine (Varian, 2003). Paraku, seda käsitlust on vähe uuritud (Dobusch, 2007).

Dahan ja Srinivasan (2000) leiavad, et jätkuvalt on vajadus odava, efektiivse ja usaldusväärse uue toote kontseptuaalse prototüübi (kontseptsiooni) testimise järele. Trott (2008) toetab samuti mõtet vajadusest süsteemse ja reeglistatud tootearenduse järele.

Eelistusanalüüs (Stated preference analysis e. Conjoint analysis) esindab üht peamist toote kontseptsiooni arendamise instrumentidest. See on UTA-s kasutatava tootekontseptsiooni katsetuspõhise prototüüpimise oluline osa. Green ja Srinivasan (1990a, 1990b), Green ja Krieger (1991) väidavad, et eelistusanalüüsil on mitmesugused eelised kliendieelistuste mõõtmisel. See eeldab, et toode või teenus on kirjeldatav kogumina kontseptuaalsetest komponentidest *atribuutidest*, millest igaühte konkreetses prototüübis esindab mitte enam kui üks *element* (Krieger et al, 2004; Moskowitz et al, 2005). Esitades kontseptsioonide seeriaid arvukatele küsitletavatele ja leides eelistatumad, eelistusanalüüs võimaldab määrata iga elemendi kasulikkuse skoori (Kessels et al, 2008).

Üheks mõnede statistikute poolt hiljuti uuritud lähenemisviisiks on Bayesi meetod. Ehkki meetod täiustab eelistusanalüüsi, on see oluliselt arvutusmahukam (osaliselt seoses Markovi ahela rakendamisega Monte Carlo valimile) ja nõuab kõrgetasemelist statistika valdamist (Marshall ja Bradlow, 2002).

Lisaks üksikutele elementidele, võivad kliendi eelistusele või ostukavatsusele avaldada täiendavat mõju nende elementide mõned spetsiifilised paarikaupa kombinatsioonid. Green ja Devita (1975) ning Carmone ja Green (1981) on märkinud, kui tähtis on uurida selliseid situatsioone, mida kutsutakse interaktsioonideks, ning määrata nende kasulikkuse määra (skoori).

Ross ja Creyer (1993) arvavad, et määrates sünergilist efekti kahe elemendi (näiteks, tooteomadused UTA-s) vahel, võib koguefekt olla märksa suurem kui mõõtes iga omadust üksikuna, mis loob ilmse võimaluse tõsta toote heakskiitu tarbija poolt läbi kahe elemendi kombinatsiooni. Samuti vastupidiselt, kui kahe elemendi kombinatsioon toimib erandlikult ebasoodsalt, siis selle negatiivse efekti teadmine nii varakult kui võimalik aitab vältida pärssivaid tootemaduste variante.

Lihtsad eelistusanalüüsi meetodid ignoreerivad interaktsioone eeldusel, et need sisalduvad veel määramata elementide kombineeritud omadustes (Chrzan ja Orme, 2000). Esmalt Green (1973), siis Green ja Devita (1975), Green ja Srinivasan (1990a, 1990b) ning seejärel Aiken ja West (1991), Carroll ja Green (1995) ning Ping (1995) võtsid kasutusele üha kasvava keerukusega meetodeid. Sirgjooneline lähenemine kõigile võimalikele interaktsioonidele viib täisfaktoriaalsele planeerimisele (Campbell ja Stanley, 1966). Reaalse suurusega tootearendusprobleemide puhul genereeritud kombinatsioonide arv kujuneb küsitlusele vastamist takistavaks teguriks. Evgeniou, Boussios ja Zacharia (2002) järgi, kõigi interaktsioonide määramine kasutades olemasolevaid lähenemisviise on sedavõrd arvutusmahukas, et vajab rakendamiseks spetsiaalseid kõrgtootlusega vektor-toetusega arvuteid, mida harilikult kasutatakse tehisintelligentsi valdkonnas. See viitab vajadusele lihtsa ja töökindla meetodi järele, et määrata, kuidas kontseptsioonielementide paarid mõjutavad tarbijahuvi.

Eksperimendi kavandamine (Experimental design), kontseptsioonielementide statistilise esituse plaan (Atkinson ja Bailey, 2001), on eelistusanalüüsi metoodika alus nagu ka mõned teised eksperimendipõhised lähenemisviisid (Hunter ja Hunter, 2005). Traditsioonilises lähenemises kasutatakse eksperimendi kavandamist tooteomaduste (muutujate) hulgale, mis tekitab üh(ts)e kavandi kõigile küsitletavatele (vahel juhuslikult). Lisaks, traditsioonilises eksperimendi kavandamises kasutatakse täielikke tootekontseptsioone, kus iga kontseptsioon sisaldab kõiki tooteomadusi (Moskowitz et al, 2005). Olemasolevate eksperimendi kavandamise meetodite piiranguks on tõsised omavahel seotud statistikaprobleemid analüüsi faasis:

Moonutatud tulemused. Piiratud arv kontseptsioone põhjustab väljundi moonutuse, kuna elemendid avalduvad piiratud arvu kombinatsioonidena ja mõned potentsiaalselt väga tugevad elemendid võivad kallutada tulemusi (Rabino et al, 2007).

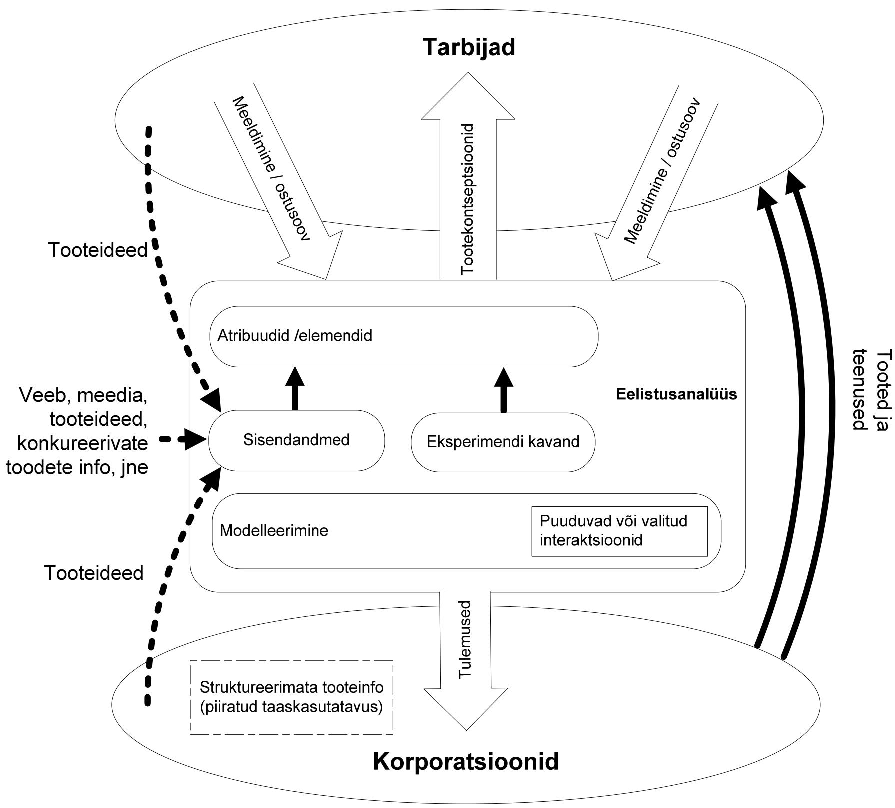
Kombinatsioonide mittetäielik varieerumine takistab (paarikaupa ja kõrgemat järku) interaktsioonide tuvastamist ning hindamist (Moskowitz et al, 2005).

Kollineaarsus. Multikollineaarsusest tulenevalt, täielikud tootekontseptsioonid ei võimalda määrata elementide kasulikkuse skoori absoluutväärtusena (Krieger et al, 2004).

Tarbijahuvi baastaseme tõese hinnangu puudumine. Selliste täielike tootekontseptsioonide statistiline analüüs nõuab efektide mudeli regressioonivõrrandeid, kus puuduvad vabaliikme hinnangud (tarbijahuvi baastase), ning elementide kasulikkus igas muutujas annab summaks nulli (Beckley ja Moskowitz, 2002).

Iga üksiku elemendi kasulikkuse skoori ühese hinnangu puudumine. Nõue, et konstantide summa oleks null, tähendab, et uue elemendi sissetoomisega uuringusse, teiste elementide kasulikkus tuleks ümber sobitada, kuna neil on suhteline väärtus. Selline ümbersobitamine ei taga andmete korduvkasutust ja nende säilitamine pole mõistlik (kasulikkuse absoluutväärtused ei ole võrreldavad teiste atribuutide või projektide tulemustega) (Beckley et al, 2007).

Senikasutatava eelistusanalüüsi metoodikal põhineva tootearenduse üldskeem on toodud Joonis 1.



Joonis 13. Eelistusanalüüsil põhineva tootearenduse üldskeem (autori joonis erinevate allikate üldistusena, sh. Krieger et al, 2004; Moskowtiz et al, 2005)

Protsess algab lähteideede (tooteomadused, seonduvad emotsionaalsed sõnumid, komponentide kujutised) kogumisega klientidelt (saadud fookusgrupilt või mõnel muul kvalitatiivsel meetodil), ettevõtetelt (ajurünnak, ideede genereerimine, sisemised uuringud, konkurentsi analüüs) ja meediast (veeb – reklaamid, blogid). Algideed koondatakse lühiteksti või mõnda teise sõnumikandjasse moodustades tooteelemendid (tooteomadused) grupeerituna sarnaste omadustega atribuutidesse. Näiteks, uute küpsisetoodete atribuudid ja elemendid võivad olla (elemendid on toodud sulgudes peale atribuute): „Maitse" („šokolaadimaitseline", „apelsinimaitseline", „maasikamaitseline"); „Suurus" („paras amps", „ülemõõtmeline", „paras suurus", jne.). Elemendid võivad olla enam kirjeldavad ning esitatud tekstina või graafilisel kujul.

Eelistusanalüüsis, kasutades traditsioonilist eksperimendi kavandamist, luuakse piiratud arv tootekontseptsioone ja esitatakse neid klientidele hindamiseks. Sellega määratakse tooteomaduse kasulikkuse suhtelised väärtused, mis on omavahel võrreldavad sama atribuudi elementide hulga piires.

Tingituna kontseptsioonide vähesest variatiivsusest, mõne elemendi tugevus võib mõjutada kogu andmestiku usaldusväärsust. Lisaks, olemasolevad meetodid kas ignoreerivad nende elementide interaktsioone või testivad neid piiratud hulgal, kuid ei võimalda neid kõiki avastada. Tooteomaduse kasulikkuse suhtelise väärtuse määramine ei võimalda struktureeritud ja korduvkasutatavat informatsiooni, mis oleks võrreldav teiste projektide või isegi teiste atribuutide infoga. Eeltoodud piirangud mõjutavad kogu meetodi kasutatavust.

UTA metoodikaid on teadlased uurinud põhjalikult peamiselt tööstuslike rakenduste tarbeks (Burchill ja Fine, 1997; Calatone ja Cooper, 1979; Cooper ja Kleinschmidt, 1995, 1996; Ford ja Sternman, 1998). Vähe on toidukaupade arendamise alaseid töid (Stewart-Knox ja Mitchell, 2003), iseäranis küpsusfaasis toodete kategoorias. Ehkki olulist uurimistööd on tehtud eelistusanalüüsi valdkonnas üldiselt (Rosenbaum, 1987; Hauser, and Rao, 2003; Toubia, Simester, Hauser, and Dahan, 2003; Krieger, Green and Wind, 2004; Orme, 2006), puudu on uuringumetoodikatest, mis leiavad elementide mistahes üksikuid ja kõiki interaktsioone. Samuti on puudu tootearenduses kasutatavatest meetoditest tooteomaduste ja -sõnumiga seotud kliendieelistuste struktureeritud ja korduvkasutatava informatsiooni saamiseks. Stewart-Knox ja Mitchell (2003) väidavad, et toidutööstuse madal innovatiivsus ja toodete turule toomise kõrge ebaõnnestumise tase viitavad tootearenduse meetodite kiire täiustamise vajadusele.

Dissertatsioonis uuritakse olemasolevaid ja arenevaid eelistusanalüüsil põhinevaid tarbijakeskseid tootearendusmeetodeid küpsusfaasis toidukaupade klassis (Uuringud I–III); uuritakse tooteelementide vaheliste üksikute ja paljude interaktsioonide avastamise ning määramise viise tootearenduse rakendustes (Uuringud I ja II), ning formuleeritakse ettepanekud struktureeritud ja korduvkasutatava tooteomaduste ja -sõnumitega seotud kliendieelistuste info loomiseks toidutööstuse tootearenduses (Uuringud II ja III).

Uuringu eesmark ja ülesanded

Käesoleva dissertatsiooni **eesmärk** on välja arendada eelistusanalüüsil põhinev kliendi kaasatust parandav tootearenduse metoodika.

Dissertatsiooni eesmärgi täitmiseks on püstitatud järgmised ülesanded:

Ülesanne 1: Välja selgitada kliendikeskse eksperimenteeriva tootearendusmetoodika arendusvõimalused.

Ülesanne 2: Täiustada kliendikeskse eelistusanalüüsil põhineva tootearendusmetoodika teoreetilist käsitlust.

Ülesanne 3: Uurida väljatöötatavate tootearendusmeetodite praktilisi rakendusi küpsusfaasis toidukaupade näitel.

DISSERTATSIOONI TEOREETILINE TAUST

Käesoleva töö üldine teoreetiline taust on avatud ülaltoodud valdkonna ülevaates ja see põhineb suures osas Aiken ja West (1991), Moskowitz (1994), Dahan ja Srinivasan (2000), Krieger, Green and Wind (2004), Moskowitz, Porretta ja Silcher (2005) ning paljude teiste töödel, mida käsitletakse põhjalikumalt dissertatsiooni teoreetilises osas. Alljärgnevalt keskendutakse teema spetsiifilisemale käsitlusele, mis osaliselt põhineb autori ja tema kolleegide panusel eelistusanalüüsi metoodika arendamisse.

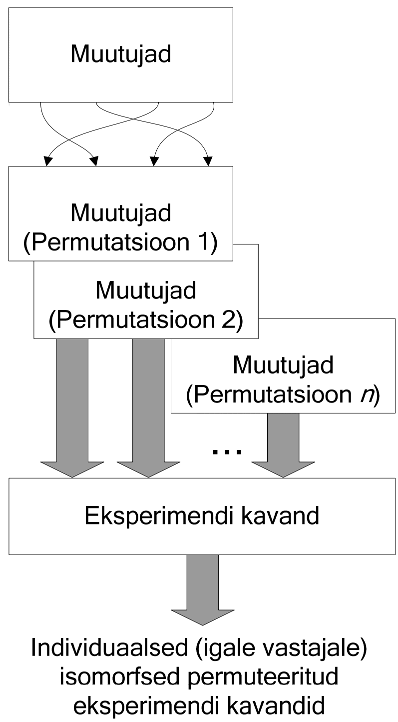
Uue toote arendamise kriitiliseks sammuks on turule toodava toote kontseptsiooni valik paljude võimalike hulgast. Dahan ja Srinivasan (2000) märgivad, et tootearenduses on suur vajadus lõppturgu põhjalikult peegeldavate tootekontseptsioonide odava paralleel-testimise metoodika järele.

UTA protsessis kasutatakse sageli eksperimendi planeerimise metoodikaid, mis on eelistusanalüüsi aluseks. Ületamaks eelmises osas kirjeldatud eksperimendi planeerimise metoodilisi piiranguid, dissertatsioonis avatakse *isomorfse permuteeritud eksperimendi kavandamise* (IPEK) metoodika (Joonis 2).

IPEK metoodikaga luuakse muutujate ja tasemete (vastavad atribuutidele ja elementidele eelistusanalüüsis) permutatsioon enne eksperimendi planeerimise metoodika rakendamist. See võimaldab luua igale testis osalejale eristavad statistiliselt isomorfsed eksperimendi kavandid. Ühtlasi võimaldab see igale testis osalejale luua tuhandeid unikaalseid tootekontseptsioone ühe eelistusanalüüsi projekti raames (sõltuvalt elementide ja permutatsioonide hulgast). *Interaktsioonid* leiavad aset, kui kahe atribuudi kombineeritud efekt erineb nende peaefektide summast. Mitmed autorid on uurinud interaktsioone (Green, 1973; Aiken ja West, 1991; Ross ja Creyer, 1993; Ping, 1995; Chrzan ja Orme, 2000; Toubia et al, 2003; Lusk ja Norwood, 2005), kuid teemat pole seni täielikult lahendatud suurema ulatusega projektides, nagu tuleneb käesolevas väitekirjas tehtud analüüsist.

Interaktsioone võib käsitleda kahel erineval viisil:

1. *Ilmutatud interaktsioonid (sünergismid, pärsingud)*: elementide paarid, mille kombinatsioonid tekitavad statistiliselt olulisi vabaliikmeid regressioonivõrrandis või hälvete analüüsis.
2. *Varjatud (ilmutamata) interaktsioonid*: interaktsioon on käsitletav kui mõne sõltuva muutuja tingimuste efekt (näit., uuritava toote omadused teiste elementide funktsioonina).



Joonis 14. Isomorfse Permuteeritud Eksperimendi Kavandamise/Kavandi (IPEK) kontseptuaalne mudel (autori joonis Moskowitz, H.R., and Gofman, A. 2005. U.S. Patent Application Serial No. 11/032,834 System and method for performing conjoint analysis. U.S. Patent Application Publication No. 2005/0177388 põhjal)

Kuna kliendid testivad iga elementide kombinatsiooni erinevates kontseptsioonides siis IPEK viib ilmutatud interaktsioonide avastamiseni. Protsess toimub sammudena, näitamaks nii interaktsioonide olemasolu kui ka tugevust ja suunda, järgmiselt:

- Loo sisendandmestik. Iga väärtusrida esindab ühe testis osaleja kontseptsiooni. Selle maatriksi veerud vastavad kontseptsiooni elementidele, ‘0’, kui element puudub ja ‘1’, kui element sisaldub kontseptsioonis.
- Regressioonanalüüsiks: kliendi hinnangud on sõltuvateks muutujateks ja lineaarsed suhted (elemendi olemasolu või puudumine) ning rist-

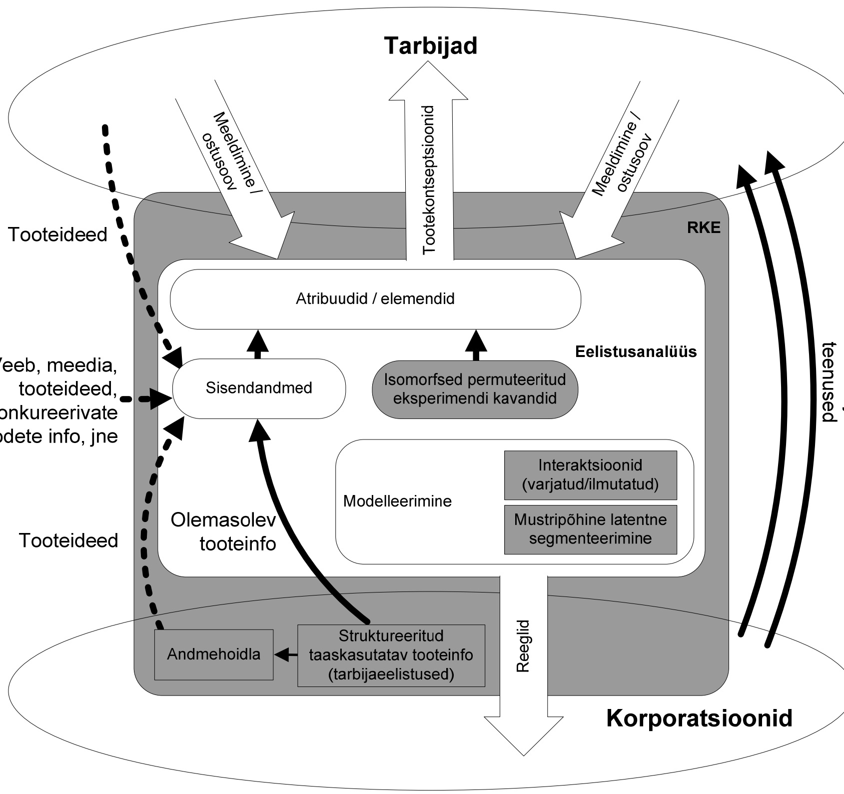
suhted (interaktsiooni olemasolu või puudumine elementidepaari vahel) on sõltumatudeks muutujateks.

- Tuvasta *kandidaat-interaktsioonide seosed* esialgsest analüüsist. Kõik interaktsioonid pole asjakohased. Selleks, et olla seose kandidaat, peab see lisama olulist ennustatavust lineaarsete seoste võrrandile. Olulisust võib määrata kasutades F-kriteeriumit.
- Moodusta lineaarne regressioonivõrrand, mis võimaldab sisestada ükskõik milliseid kandidaat-seoste paare, kui interaktsiooni tingimused selgitavad statistiliselt täiendavat variatiivsust väljaspool lineaarseid seoseid.
- Võrdle interaktsioone mittearvestavat lineaarset seost nendega, mis arvestavad interaktsioone. Harilikult ainult vähesed interaktsiooni seosed annavad olulist lisa kontseptsiooni kasulikkuse skoori varasemale tulemusele (vt Uuringud I ja III).

Eelkirjeldatud eelistusanalüüsi metoodika täiustusi rakendatakse autori poolt Reegleid kujundava eksperimenteerimise (RKE) meetodi väljatöötamiseks. RKE on struktureeritud metoodika tarbijakeskseks kontseptuaalsete prototüüpidega eksperimenteerimiseks, mis on kasutatav nii tootearenduses kui ka teistes valdkondades. Klassifitseerimise seisukohalt RKE lähtub kliendikesksest proaktiivsest lähenemisviisist struktureeritud eksperimenteerimisele, uurides tarbija eelistusi kontseptsiooni tasemel, kasutades eelistusanalüüsi mittetäielikele kontseptsioonidele (null-tingimustega kontseptsioonid), mis põhinevad eri tüüpi osaliste peaefektidega eksperimendi kavanditel (isomorfsed permuteeritud eksperimendi kavandid). RKE analüüsib latentset segmenteerimist (Green ja Krieger, 1991) koos ilmutatud kujul interaktsioonide avastamisega (Green, 1973) ning varjatud interaktsioonide uurimisega.

Laiemas mõistes, RKE on süsteemne lahendusorientatsiooniga eksperimendiprotsess, mis kujundab, testib ja modifitseerib alternatiivseid ideid, pakendeid, või teenuseid korrastatud viisil kasutades eksperimendi kavandit nii, et arendaja ja turundaja avastavad reeglid ja mustrid, mis näitavad, mis meeldib kliendile lahendusena, isegi siis, kui klient ei oska sõnastada oma vajadust. (PDMA, 2007).

Joonis 3 selgitab pakutava metoodika – reegleid kujundava eksperimenteerimise (RKE) kontseptuaalset skeemi. Sisendandmed on jagatud atribuutidesse ja elementidesse, mis on jaotatud IPEKi põhjal eksperimentaalselt kujundatud *n* kontseptsiooni. Protsess käivitub osaliselt samadest algideede allikatest nagu traditsioonilisel meetodil. Lisaks, võidakse kasutada struktureeritud infot varasemast RKE rakendusest, mida meetod võimaldab salvestada ja võrrelda üle erinevate projektide. Kontseptsioone on testitud klientide peal eelistusanalüüsi käigus, mille tulemusena on saadud kasulikkuse skoori absoluutväärtused. Kuna IPEK võimaldab kontseptsioonide variatiivsuse kasvu, RKE tuvastab ilmutamata ja ilmutatud interaktsioonid. Individuaalsed mudelid soodustavad samuti mustripõhist latentset segmenteerimist. Seega, RKE metoodika võimaldab kujundada reeglid (suunad) UTA-ks korporatsioonis – saadakse kogum kvantitatiivseid suhteid RKE elementide, kliendieelistuste ja suuniste vahel, kuidas tõsta kliendile meeldivust (ostusoovi) erinevate stsenaariumide korral.



Joonis 3. Modifitseeritud eelistusanalüüsi meetodi kontseptuaalne skeem – reegleid kujundav eksperimenteerimine (RKE). Eelistusanalüüsil põhineva kliendikeskse tootearenduse meetodi uuendused on esitatud varjutatuna (autori joonis)

RKE põhineb IPEKil, mis loob hulgaliselt permuteeritud kavandeid, elimineerides traditsiooniliste lähenemisviiside piiranguid: võimalik andmete moonutus, suhtelised kasulikkuse skoori väärtused, alusjoone määrangu puudumine ja suutmatus tuvastada tooteomaduste (elemendid eelistusanalüüsis) vahelisi ilmutatud interaktsioone. Lisaks, RKE võimaldab varjatud interaktsioonide analüüsi, andes disaineritele ja turundajatele võimaluse tuvastada, kuidas tooteomaduste asendus majanduslikult ja tehnoloogiliselt mõistlike alternatiividega juhib kliendi taju teiste tunnuste suhtes. Individuaalsed unikaalsed kavandid loovad aluse klientide mustripõhiseks latentseks segmenteerimiseks. Seda tüüpi segmenteerimine, teadaolevalt, annab enam sihtmärgistatud lahendusi, kuna identifitseerib latentseid sarnase mõtteviisiga kliente (Krieger et al, 2004).

Lisaks eeltoodule, RKE võimaldab tuvastada interaktsioone elementide vahel ning tekitada “mis-siis-kui” analüüse tooteomaduste asenduseffektide mõjust eelistusanalüüsi teistele aspektidele kui ka üldistele kliendieelistustele.

Erinevalt traditsioonilise meetodi tulemustest, millel on piiratud toimeulatus, käesolev terviklik kogum korduvkasutatavaid ja võrreldavaid kvantitatiivseid seoseid RKE elementide ja tarbijaeelistuste vahel tekitab enam kasutatavaid juhiseid, kuidas tõsta kliendile meeldivust (ostukavatsust) eri stsenaariumide toimimisel. Üheskoos võib neid kasutada kui reegleid UTA-ks luues struktureeritud juhendid arendajaile. Kasulikkuse absoluutväärtus võimaldab tulemuste kogumist tulevikus kasutamiseks kui ka võrdlusteks ja taaskasutuseks. Uuringus II näidatakse, et see soodustab tooteuuendusprotsesse.

Uuringus III analüüsitakse innovatsiooniprotsessi küpsiste kui küpsusfaasis toidukaupade näitel. Andmehulk 1 Uuringus III koosneb kuuest atribuudist kuue elemendiga neist igas (vt. Tabel 1 Uuring III). Elemendid kirjeldavad küpsiste erinevaid omadusi. *Elementide olemus* tootearenduse eelistusanalüüsis peab olema spetsiifiline. Toidukaupade puhul on elementidel konkreetne sisu. Roheline värvus, magus maitse, viirutusega kujundus, tihe struktuur – need kõik on konkreetse sisuga omadused. Arendaja saab neid kasutada kui värvisegu sõnalise pildi kujundamiseks. Võrdluseks, fraasid nagu ‘hea maitse’, ’rammus jook’, ‘lõbus kogemus’, ‘vanainimese küpsis’ on vähem asjakohased juhised uuenduse varases faasis, kuna need ei märgi konkreetset omadust, mida saaks varieerida. Need emotsionaalsed ja ebakonkreetsed omadused võivad olla kasutusel positsioneerimisel (turunduses), kuid mitte arenduses.

Testkontseptsioonid sisaldavad lühikesi kombinatsioone, milles igal kontseptsioonil on kolm või neli elementi, millest ilmutatakse ainult ühte elementi konkreetsest atribuudist eksperimendi kavandis konkreetsele kontseptsioonile. Eksperimendi kavandeid permuteeritakse süstemaatiliselt saades 400 erinevat kavandit, mis kõik on baaskavandiga isomorfsed. See kavandamise funktsioon tagab, et peaaegu kõik testis osalejad hindavad erinevaid kombinatsioone, välistades ootamatult tugeva mõjuga elementidest tingitud tulemuste moonutusi. Süstemaatiline kavandi permutatsiooni strateegia võimaldab samuti tuvastada kontseptsiooni elementide omavahelisi paaris-interaktsioone.

Testis osalejatele esitatakse üks kontseptsioon korraga, nad hindavad tootekontseptsiooni fikseeritud üheksa-pallises skaalas ’Kuivõrd need küpsised huvitavad teid?’ Vastajatelt kogutud hinnangud (sõltuv muutuja) koos eksperimendi põhikavandiga (sõltumatud muutujad) on sisendiks (tavalisele vähimruutude) regressioonianalüüsile, mis määrab üksikute elementide kasulikkused kliendi hinnangu põhjal.

RKE rakendamise näide

Protsessi illustreeritakse Uuringu III näitel (Andmestik 1). Peale sisendandmestiku kogumist ja üksikelementidele vormindamist (vt. Appendix F), need sisestatakse RKE programmi, näiteks Ideamap.NET (vt. Appendix E: demoprojekti ekraanivaated). Kuna see elementide kogum sisaldab kuut atribuuti kuue elemendiga neist igas, on vastav originaalne eksperimendi kavand valitud vastavalt sellele spetsiifilisele elementide kogumile (Appendix G). Statistika kirjandusest on teada erinevaid kavandite/kavandamise allikaid kasutades selliseid tarkvara pakette nagu SPSS (SPSS, 2007). Permutatsioonimoodul kasutab originaalset eksperimendi kavandit permuteeritud (iga üksiku testis osaleja) atribuutide ja elementide kogumile. Lisas (Appendix A) on toodud kaks permuteeritud kavandit osalejatele 1 ja 2 kasutades IPEK meetodit. Tabelis sisalduvad samuti vastajate hinnangud igale üksikule kontseptsioonile, mis vastavad igaüks testdisaini reale eksperimendi kavandis.

Järgmise sammuna testis osalejad hindavad üksikutele permuteeritud testikavanditele vastavaid kontseptsioonide kogumeid andes hinnangu (meeldivuse tase) igale kontseptsioonile. Kogutud andmeid analüüsitakse regressioonimoodulis (elemendid on sõltumatud ja hinnangud on sõltuvad muutujad) kalkuleerimaks iga elemendi individuaalset kasulikkust igale vastajale.

Võtmeks andmete mõistmisel tootearenduse ja innovatsiooni seisukohalt on üksiku elemendi kasulikkuse skoor. Elemendi kasulikkuse põhjal saab arendaja sünteesida uusi ja potentsiaalselt edukaid/läbimurdelisi küpsisekontseptsioone. Tasemeni, kus kontseptsiooni elemendid toimivad ainult tagasihoidlikult, kontseptsioon pole edukas. Kasulikkuse interpreteerimise normväärtused ja vabaliikmed on toodud Tabel 1.

Tabel 5. Kasulikkuse ja vabaliikme normväärtused (allikas: Moskowitz et al, 2005)

Vabaliige	*Interpretatsioon*
>60	Vastajad on väga vastuvõtlikud tootele
50–60	Ligikaudu pool vastajatest on väga positiivsed
40–50	Vastajad aktsepteerivad ideed
30–40	Elemendid vajavad läbitöötamist
<30	Toode on tavakaup ja elemendid tuleb läbi töötada
Kasulikkuse määr	*Interpretatsioon*
>15	Element toimib erandítult hästi, tugev läbilöök
10–15	Element toimib hästi
5–10	Elemendil on läbilööki
0–5	Element on vaevu, kui üldse, toimiv
<0	Element kahjustab aktsepteeritavust aktiivselt

Arvväärtused tabelis on tingimuslik tõenäosus (%), et inimesed huvituvad kirjeldatud toote ostmisest. Eelistusanalüüsi vabaliige mittetäielikes kontseptsioonides on vastajate tooteideest huvitatuse lähtetase (ilma ühtegi elementi esitamata).

Andmestik 1: 439 testis osalejat hindasid 60 individuaalselt varieeritud kontseptsiooni, mis genereerisid kasulikkuse näitajad, nagu need on esitatud Tabelis 3 (Uuring III). Vabaliige 34 näitab, et ligikaudu 34% vastajatest hindab kontseptsiooni huvipakkuvaks. See 34% on oluliselt madalam näitaja kui 45% vastajatest, kes hindaksid kontseptsiooni huvipakkuvaks, kui seda positsioneerida (Andmestik 2 ja 3) suupistena või külalistele serveerituna. Seetõttu, positsioneerimisel on suur üldeffekt. See tähendab, et ilma lõppkasutust positsioneerimata, peavad elemendid toimima tugevamalt veenmaks vastajat huvituma kontseptsioonist.

Loomaks edukat kontseptsiooni kogu paneelile Andmestikus 1 (keskmistatud üle kõigi testis osalejate), arendaja peaks valima kõrgeima väärtusega elemendid igast atribuudist. Määratud tarbija huvi skoori (kontseptsiooni kasulikkuse määr) saab konstrueerida summana vabaliikmest ja valitud elementide kasulikkusest (Appendix F):

$$C_{t1} = A_1 + B_1 + C_4 + D_3 + E_3 + F_1 = 34 + 8 + 7 + 5 + 11 + 6 + 5 = 76,$$

kus C_{t1} – optimaalse kontseptsiooni skoor kogu paneelile (Andmestik 1); A_1 – atribuudi A element 1; B_1 – atribuudi B element 1, jne.

Võrdluseks, tarbijahuvi määratud Andmestik 2 põhjal:

$$C_{t2} = A_4 + B_5 + C_5 + D_3 + E_4 + F_1 = 45 + 6 + 5 + 2 + 8 + 3 + 1 = 70,$$

kus C_{t2} – optimaalse kontseptsiooni skoor kogu paneelile (Andmestik 2).

Kui arendaja eksikombel valib madalaima skooriga elemendid (näit.: kui eelistusanalüüsi ei kasutata ja valik tehakse erapoolikult), tuleks tarbijahuvi skoor järgmine:

$$C'_{t1} = A_2 + B_2 + C_3 + D_2 + E_2 + F_6 = 34 + 1 + (-1) + 2 + (-9) + 2 + 2 = 31,$$

kus C'_{t1} – kontseptsiooni skoor kogupaneeli (Andmestik 1) madalaima skooriga elementide puhul. See tähendab, et arendaja ei kasuta struktureeritud eksperimendikavandit ja valib juhuslikult madalaima skooriga elemendid, mille tulemusena kontseptsiooni tarbija ostuhuvi tingimuslik tõenäosus on ca 60% madalam kui C_{t1} (kõrgeim skoor).

RKE kasutab süstemaatiliselt permuteeritud kavandeid, võimaldades arendajal tuvastada tooteomaduste kombinatsioone, mis ilmutavad ebaharilikult kõrgeid või ebaharilikult madalaid skoore võrreldes sellega, mida võiks oodata lihtsate interaktsioonideta mõjude puhul. Võime tuvastada tugevaid interaktsioone suures kombinatsioonide hulgas annab tootearenduseks eriti võimsa vahendi, millega arendustegevust kiirendada, sest see näitab, millised elementide kombinatsioonid tõesti 'töötavad koos'. Meetod erineb põhjalikult tavapärasest eelistusanalüüsist, millega saab testida vähest arvu interaktsioone, kui need on 'sisse ehitatud' analüüsi alguses (viis kuni kümme interaktsiooni). Uuringu III projektis kasutatakse kuut tooteomaduste atribuuti, kuue elemendiga atribuudi kohta, 15 paari atribuute, 36 interaktsiooni paari kohta, ehk kokku 540 interaktsiooni, mille testimine tavapäraselt pole teostatav.

Selles projektis (detaile vt. Uuring III) on ainult neljal elemendipaaril tugev sünergiline effekt: E_2+F_2, A_6+E_6, B_3+F_3 ja C_6+E_3. Näiteks, elementide kombinatsioon A_6 (*Jumbo size… for when you want a little extra*) ja E_6 (*Comes in a crush-proof box… no more broken cookies*) mudelis, mis ignoreerib interaktsioone (tavameetod) saadakse neutraalsed kasulikkused +2 iga elemendi kohta vabaliikmega +35. Need numbrid (skoorid) viiksid järeldusele, et see ei ole väga efektiivne tooteomaduste kombinatsioon, kuna vähem kui 40% vastajatest arvaksid seda ostvat. Täpsem IPEK-it kasutav RKE mudel kontrollib kõiki võimalikke interaktsioone projekti elementide vahel. Sel juhul on interaktsioonide mõju palju suurem kui kasulikkused üksikuna, andes kontseptsiooni (konstandi ja individuaalsete kasulikkuste ning interaktsiooni effekt) skooriks +59. See number näitab, et peaaegu 60% vastajatest arvavad ostvat seda toodet.

Lisaks, kuna RKE annab kasulikkuse absoluutväärtused, on võimalik erinevate omaduste kasulikkusi omavahel võrrelda, kuid saab võrrelda isegi sama tüüpi tarbijate ja sarnase struktuuriga projekte. Näiteks, see võimaldab võrrelda kasulikkust ja vabaliikme konstanti Andmestikes 1, 2 ja 3 Uuringus III.

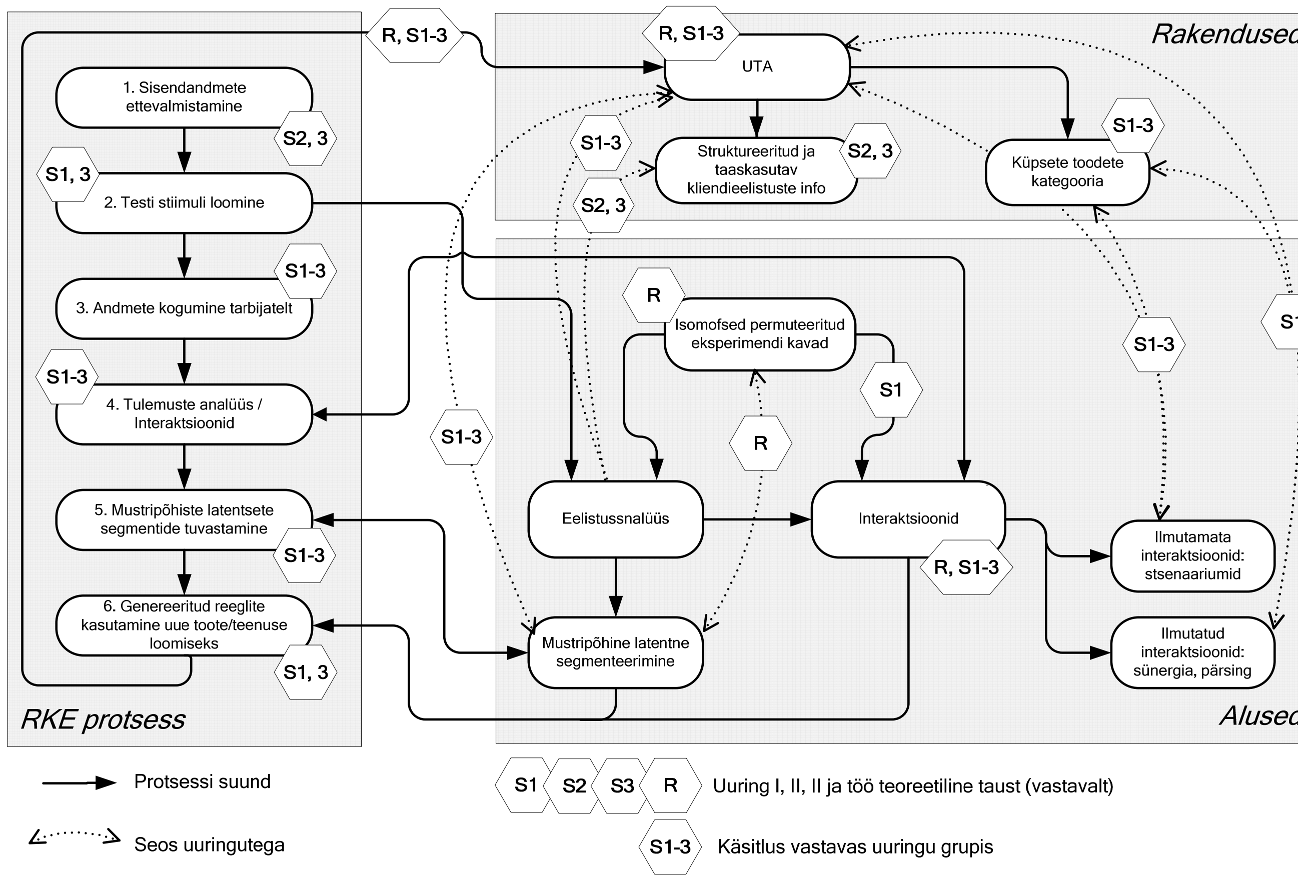
Kokkuvõtteks, võrreldes seniste eelistusanalüüsi rakendustega, RKE annab enam usaldusväärsed tulemused, mida saab koguda, salvestada ja taaskasutada. Leitud kvantitatiivsed seosed elementide vahel sisaldavad iga elemendi panust tarbijaeelistustesse kui ka seaduspärasusel põhinevat latentset e. vaiksegmenteerimist, ilmutatud interaktsioone ja stsenaariume (ilmutamata interaktsioonid).

Kõige sagedamini kasutatavaks RKE vahendiks (dissertatsiooni kirjutamise ajal) on veebi-põhine tarkvara kui teenus (Software as a Service – SaaS) Ideamap.NET (www.ideamap.net), mille autor arendas välja oma töö varasemast versioonist Ideamap® ja PC-põhisest eelistuanalüüsi vahendist Ideamap® Wizard. Ideamap.NET kasutab täielikku isomorfse permutatsiooniga eksperimendi kavandit igale individuaalsele vastajale. See sisaldab kirjeldatud meetodit kindlustades automaatse permuteeritud disaini, andmekogumise ja analüüsi, sh segmenteerimise. Lisades (Appendix E) on toodud selle instrumendi töökeskkonna kujutis arvutiekraanil.

DISSERTATSIOONI STRUKTUUR JA UURIMISMUDEL

Käesoleva dissertatsiooni uurimismudel on esitatud Joonis 4. Mudeli kolm põhiosa (Protsess, Rakendused ja teoreetilised Alused) on uuringutes omavahel tihedalt seotud. Dissertatsiooni iga uuring käsitleb vähemalt kahte nendest kolmest aspektist. RKE põhialused on esitatud uuringu teoreetilise tausta käsitluses kui ka järgnevas kolmes publikatsioonis. Täiendavat materjali võib leida ka autori teistes publikatsioonides (näiteks, Moskowitz ja Gofman, 2003, 2007).

RKE teoreetilised alused põhinevad eelistuanalüüsil, kujundipõhisel latentsel segmenteerimisel ning interaktsioonide avastamisel ja analüüsil. Kõik need omakorda põhinevad permuteeritud isomorfsetel eksperimendi kavanditel (IPEK). Seoseid teoreetiliste aluste komponentide vahel erinevates aspektides on käsitletud kõigis kolmes uuringus. Aluste süvakäsitlus on toodud uuringus I. Uuring II käsitleb RKE üldist raamistikku küpsusfaasis tooteklassi arendusvõimaluste avastamise näitel. Uuring III jätkab käsitlust ja laiendab seda innovatsiooniprotsessile küpsusfaasis toodete arenduses.



Joonis 4. Uurimismudel – Seosed RKE teoreetiliste Aluste, Protsessi ja Rakenduste vahel (autori joonis)

RKE protsess on esitatav kuue universaalse sammuna, mis sisaldavad osaliselt eelistusanalüüsi projektides harilikult kasutatavaid tegevusi, kuid juba modifitseeritud kujul (vt. Appendix C, Joonis A-1) laiendades meetodit erinevatesse valdkondadesse. Neid samme on uuritud teoreetilise tausta käsitluses Uuringus I ja arendatatud Uuringutes II ja III. Uuringud I – III demonstreerivad protsessi küpsusfaasis toote arendamise kontekstis. Uuring I uurib sügavuti uusi lähenemisi interaktsioonide avastamisele eelistusanalüüsis. Uuring näitab üksiku ja kõigi interaktsioonide avastamise tähtsust ning meetodeid RKE protsessis ja on ühtlasi selle lähenemisviisi teoreetilise ja metoodilise käsitluse põhiallikaks.

Teoreetiliste aluste osa on tihedalt seotud RKE protsessiga (Joonis 4: sammud 1, 2, 4, 5, 6), kõik uuringud käsitlevad neid etappe. Uuringud II ja III pööravad olulises osas tähelepanu sisendandmete ettevalmistuse etapile. Testkontseptsiooni loomist, andmete kogumist, tulemuste analüüsi ning interaktsioonide ja kujundipõhise latentse segmenterimise etappe käsitletakse kõigis uuringutes. Viimast sammu, genereeritud toote või teenuse loomise reeglistikku käsitletakse Uuringutes I ja III.

PUBLIKATSIOONID

Uuring I. Stsenaariumid, sünergismid ja pärsingud – käsitlemata eelistusanalüüsis

Gofman, A. 2006. Emergent Scenarios, Synergies, And Suppressions Uncovered within Conjoint Analysis. Journal of Sensory Studies, 21(4): 373–414.

UURING I tutvustab kaht lähenemist interaktsioonide suuna ja tugevuse tuvastamisele eelistusanalüüsis. Mõlemad käsitlused kasutavad eksperimendi kavandi peaefekte, mida on permuteeritud, loomaks sadu algse kavandi struktuuriga isomorfseid uusi kavandeid (IPEK). Esimeses lähenduses stsenaariumi analüüs loob vastastikku erandlikult eristuvaid ja põhjalikke spetsiifiliste elementidega kontseptsioonide alagruppide kogumeid, esitab vabaliikmega regressiooni igas alagrupis ja tuvastab ühe elemendi mõju teiste kasutatavusele. Teises lähenemises täielike lähteandmete koosmõju analüüsiga kehtestatakse lineaarsed tingimused üksikutele elementidele ja lubatakse olulisi paariskombinatsioone, kui need lisavad olulist täiendavat ennustatavust mudelile. Need kaks käsitlust tuvastavad mõju olemasolu ja seejärel mõõdavad ühe elemendi kasulikkuse skoori mõju teistele (stsenaarium) ja ootamatuid kahe kontseptsioonielemendi kombinatsiooni efekte (interaktsioonide analüüs). Käsitlust illustreerivad kaks kaasust: apelsinijoogi maitse ja karastavuse kommunikeerimine ja küpsiste eelistatavate tunnuste tuvastamine.

Uuring II. Kõrgetasemeliste kliendiuuringu meetodite kasutamine instrumendi-põhise juhendi ja andmebaasi loomiseks tootearenduses ja turunduses
Moskowitz, H., Gofman, A., and Beckley, J. 2006. Using High-Level Consumer-Research Methods to Create a Tool-Driven Guidebook and Database for Product Development and Marketing. Journal of Sensory Studies, 21(1): 54–100.
UURINGUS II uuritakse tootearenduses kasutatava informatsiooni ja instrumendi-põhise andmebaasi erinevaid aspekte. Eesmärgiks on luua meetod, mille abil saaks tootekontseptsioonide ja toodete alast teadmust arhiveerida, kasutades spetsiifiliste tootekategooriate ülevaateid. Andmebaas sisaldab tootekontseptsioonide süsteemset analüüsi, sh nii tooteomaduste kui emotsioonidega seotud elemente. Andmebaasis salvestatud kontseptsioonid annavad samuti ülevaate testis osalejate vastustest tooteomadustega seotud väidetele, sh emotsionaalsetele elementidele ja brändidele, püüdes kujundada mudelit, mis näitab kuidas erinevad kontseptsiooni elemendid (tooteomadused) juhivad kliendihuvi.

Uuringu teises osas tehakse maitse analüüsi toodete konkurentsi raamistikus enne süsteemse tootearenduse käivitamist. Selles osas tuvastatakse oodatava ja rahuldava „toote-maitse" omaduste vahemikud, tüüpiliste toodete heakskiidu tase, seosed meeldimise ja maitseomaduste vahel ning segmenteeritakse maitseeelistused. Tootearendajad saavad kasutada neid kahte osa koos. Meetod on kasutav samuti olemasoleva teadmuse arhiveerimiseks, andmelevi ergutamiseks ja info jagamiseks. Mõlema osa põhieesmärk on võimaldada tootearenduses palju efektiivsemalt kasutada ennemini klientide ühiskogemust kui ekspertide teadmist, tegemata kompromissi korporatiivse teadmuse spetsiifiliste koostisosade, protsesside või ärivõimalustega.

Uuringu empiiriline osa käsitleb tootearenduseks struktureeritud andmebaasi kaasatava info tüüpe, eriti küpsete toidutoodete kategoorias. Selle uuringuosa eesmärk on mõista vaniljejäätise meeldimise käivitajaid läbi kliendieelistuste teadasaamise esindusliku valiku kaudu (22 vaniljejäätise varianti). Sellised eesmärgid on tüüpilised hinnangu-uuringute kategoorias uue toote arendamise algstaadiumis.

Uuring III. Suundudes kliendikesksele innovatsioonimasinale 'tavaliste' toodete kategooriates nende hilises elutsükli faasis
Gofman, A., and Moskowitz, H. 2009. Steps towards a consumer-driven innovation machine for 'ordinary' product categories in their later lifecycle stages, International Journal of Technology Management, 45(3/4): 349–363.
UURING III käsitleb innovatsiooni nende toodete kategooriates, mida tüüpiliselt peetakse küpsusfaasis olevateks. Kasutatakse eelkirjeldatud RKE unifitseeritud struktuurset käsitlust ja raamistikku. Analüüs selgitab välja arendajate poolt leitud tooteomaduste kliendieelistused. Järgnevalt uuring tuvastab võimalused mõlemas aspektis: varieerides testis osalejate ülesandepüstitusi (hinnates erinevaid lõppkasutusi) ja kasutades eelistuste põhist latentset segmenteerimist avastamaks uusi sarnase hoiakuga inimeste gruppe, kus tuvastatakse tegelikku innovatsioonivõimalust.

Uuringu III empiirilises osas uuritakse innovatsioonivõimalusi küpsusfaasis toodete kategoorias küpsiste näitel, laiendades Uuringus I tehtut. Analüüsitakse laia empiirilist andmestikku valimaks tooteomaduste eeliskombinatsioone, mis tõstavad kliendieelistuste ennustatavust kolme erineva kasutussituatsiooni tarbeks, sh eelistuste mustri põhine segmenteerimine ja tooteomaduste vaheline ilmutatud interaktsioon.

KOKKUVÕTE JA TULEMUSTE ARUTELU

Dissertatsioonis käsitletakse struktureeritud eksperimenteerimise kliendikeskset proaktiivset metoodikat tootearenduses. Uuring keskendub tootekontseptsioonide kliendieelistuste väljaselgitamisele ja analüüsile eelistusanalüüsi metoodikas, mis on üks peamisi instrumente toote kontseptsiooni arendamises ja on ühtlasi eksperimenteerimispõhise prototüüpimise lahutamatuks osaks. Esitades arvukale testis osalejatele tootekontseptsiooni sarju, ja leides nende hulgast enam eelistatud, eelistusanalüüsi meetod võimaldab määrata iga tooteelemendi kasulikkust.

Korporatsioonid loodavad sageli disainerite vaistule uute toodete väljaarendamises. Schroeder (2005) arvab, et edukas tootearendus sõltub disaineri (arendaja) geniaalsusest, kui see juhtub teadma, mis kliendile meeldib. Uuringud I–III näitavad kliendiuuringutel põhineva struktureeritud innovatsiooniprotsessi väärtust, vastandudes Schroederi vaadetele (kokkuvõte peamistest uuringu tulemustest on toodud Tabel 6). Dissertant on ühemõtteliselt samal meelel suure uurijate koolkonnaga, kes usub kliendieelistuste teadmise jõusse tootearenduses (Moskowitz et al, 2005; Malhotra ja Segars, 2001) kui ka kliendikesksesse süstematiseeritud ja reeglistatud tootearendusse (Trott, 2008). Uuringute I ja III empiirilised tulemused demonstreerivad tootearendajale kättesaadava olulise informatsiooni rohkust tarbijaeelistuste teadmisele tuginevas innovatsiooniprotsessis.

Uuring I kinnitas Greeni ja Devita (1975) ning Carmone ja Greeni (1981) tulemusi, et lisaks üksikutele tooteomaduste kliendi meeldivuse või ostusoovi (kasulikkuse) skoorile mõjuvad mõned paarikaupa kombinatsioonid – interaktsioonid. Osa uurijaid kirjeldavad jätkuvalt lihtsaid eelistusanalüüsi meetodeid, mis ignoreerivad interaktsioone, eeldusel, et määramata interaktsioonide väärtused juba sisalduvad kombineeritavates tooteelementides (Chrzan ja Orme, 2000). Uuringute I ja III tulemused tõestavad, et olulised ilmutatud interaktsioonid võivad lisada 10 kuni 30 % kliendi ostukavatsuse tingimuslikku tõenäosust või seda vähendada samal määral, kui kombinatsioon osutub pärssivaks.

Eelistusanalüüsi aluseks on eksperimendi kavand. Traditsioonilised meetodid, nagu neid kirjeldavad Atkinson ja Bailey (2001) ning Hunter ja Hunter (2005), kasutavad eksperimendi kavandamist atribuutide kogumile ainult ühekordselt, luues ühekordse kavandi kõigile vastajatele (vahel juhuslikustatult).

Tabel 6. Peamiste tulemuste kokkuvõte

Uuring	Eesmärk	Valim	Tulemused
I	Uurida latentseid (ilmutatud ja ilmutamata) interaktsioone eelistusanalüüsi elementide vahel.	*Andmestik I:* 38 *Andmestik II:* 439	1. Isomorfsel Permuteeritud Eksperimendi Kavanditel (IPED) põhinev metoodika tekitab laia massiivi eksperimentaalselt kujundatud tootekontseptsioone, mis sisaldavad kõiki võimalikult ühtlaselt jaotatud kombinatsioone paarikaupa elementidest võimaldades statistiliselt testida ükskõik millist ja kõiki interaktsioone arvestades nende tugevust. 2. Enamikul juhtudel ainult väike osa ilmutatud interaktsioonidest on olulised. 3. Ilmutamata interaktsioonide analüüs tootearenduses tekitab ’mis siis kui’ tüüpi stsenaariumid omaduste asendatavusest, mis tulenevad tehnoloogilistest või majanduslikest piirangutest või ennustatavatest kliendieelistustest. 4. Olulised ilmutatud interaktsioonid võivad lisada kliendi tingimuslikku ostukavatsuse tõenäosust 10 kuni 30 protsenti või vähendada seda samal määral, kui kombinatsioon osutub pärssivaks.
II	Uurida ja täpsustada küpsusfaasis toodete kategooria tootearendusele suunatud RKE-d rakendavaid metoodikaid, kasutades info struktureeritud uuringut, arhiveerimist ja taaskasutust.	*Andmestik I:* 322 *Andmestik II:* 100	1. On vaja katsetada ja testida paljusid süsteemselt varieeritud tootekontseptsioone, et tuvastada testkontseptsioonide mustreid, mis kujundavad kliendieelistusi. 2. Tulemused näitavad, et tarbijate jaotamine latentsetesse kujundipõhistesse segmentidesse, mida võimaldavad IPEK-id, viib paremini sihtmärgistatud toodeteni kõrgema tarbijaeelistuste ennustatavusega, kui keskmised demograafiliste alagruppide analüüsi mudelid. 3. 30 toote eelistuste mustri põhise segmenteerimise uuring näitab, et kliendieelistuste mõistmine läbi eelistuste-põhise segmenteerimise võimaldab paremini eesmärgistatud UTA-t.

Uuring	Eesmärk	Valim	Tulemused
			4. Pakutav kahe-osaline (kontseptuaalne ja maitse) metoodika loob struktureeritud informatsiooni tootearendajatele. See omakorda soodustab olemasoleva teadmuse arhiveerimist selle jagamiseks ja korduvkasutuseks tootearenduses.
III	Uurida ja täiustada tooteomaduste innovatsiooni protsessi tüüpiliste küpsusfaasis toodete klassis.	*Andmestik I:* 439 *Andmestik II:* 313 *Andmestik III:* 611	1. Pakutav tooteomaduste kombinatoorikapõhise süsteemse rekombineerimise protsess, mida võimaldab RKE, soodustab innovatsiooni küpsete, sh toidutoodete klassis. 2. Pakutav innovatsioonivõimaluste identifitseerimine kasvab välja klientide mustripõhisest latentsest segmenteerimisest. 3. Kasutades omadusi, mis toimivad sünergiliselt (interaktsioon on positiivse mõjuga), küpsiste tarbijate huvitatuse tingimuslik tõenäosus kasvas 13–20 %. 4. Pakutav metodoodika loob aluse laiendamaks tekkivaid rakendusi automaatseks sisendmaterjali kogumiseks ’veebi otsingumootoriga’ ja sisu analüüsiks. See omakorda loob aluse süstemaatiliseks RKE-käivitatud poolautomaatseks tarbija-eelistuste info kogumiseks.

See võib põhjustada tulemuste moonutatust, kuna mõned tugevad elemendid võivad mõjutada reitinguid tulenedes mittepiisavast kombinatsioonide varieerumisest. Moskowitz (1994) soovitas teist lähenemisviisi permuteerides algset kava ja niimoodi luues laiemalt jaotunud kontseptsioonide kogumi ning täiustades protsessi kvaliteeti. Uuringu I tulemused kinnitasid selle viisi eeliseid *kasvatades* unikaalsete kontseptsioonide arvu. Dissertatsioon arendab edasi seda lähenemist meetodiga, mille nimetuseks pakutakse Isomorfne Permuteeritud Eksperimendi Kavandamine/Kavand (IPEK). IPEK-d loovad laia ja erilaadse kogumi kontseptsioonidest, mis sisaldavad ühtlaselt jaotatud elementidevahelisi paarikaupa kombinatsioone, võimaldades niiviisi statistiliselt testida kõiki selliseid interaktsioone arvestades nende tugevust. Sellega ületatakse veel üks seniste meetodite piirang – *kombinatsioonide vähene varieeruvus*. Uuring I näitas, et permuteeritud kavandid aitasid vähendada testkontseptsioonide piiratud arvust tulenevaid tulemuste moonutusi, mis olid omased alternatiivsetele eelistusanalüüsi meetoditele (Atkinson ja Bailey, 2001; Hunter ja Hunter, 2005). Uuringute I-III tulemused näitavad, et klientide jaotamine latentsetesse eelistuspõhistesse segmentidesse IPEK-i abil, võimaldab paremini sihtmärgistada tooteid (kõrgema kliendieelistuse tasemega) kui demograafiliste alagruppide analüüsi meetod, kinnitades Moskowitz et al (2005) tulemusi.

Koolkond eelistusanalüüsi uurijaid (Melles, Laumann ja Holling, 2000) kasutab täielike tootekontseptsioonide meetodit, milles kõik tooteomadused on omistatud kõigile kontseptsioonidele. Selle eksperimedi kavandamise lähenemisviisi puuduseks on tõsised omavahel seotud statistilised probleemid analüütilises faasis, mis võib põhjustada moonutatud tulemusi, kollineaarsust, võimetust määrata üksikute elementide huvitaseme ja kasulikkuse skoore.

Moskowitz et al (2005) kirjeldatud meetod kasutab mittetäielike kontseptsioonide käsitlust, mis lubab mõnede atribuutide puudumist valitud kontseptsioonide hulgas. IPEK-de meetod põhineb sellel käsitlusel. Uuringute I–III tulemused kinnitavad selle meetodi eeliseid. Uuringutes II ja III kirjeldatud mittetäielike tootekontseptsioonide eeliseks on võimalus andmete võrreldavuseks ja akumuleeritavuseks, mis loob eeldused tooteomaduste taaskasutatavate andmete kogumiseks ja arendajatele kiireks uuendusprotsessi käivitamiseks kui ka *tõelise huvitatuse baastaseme* ja individuaalse kasulikkuse määramiseks tänu varasemate meetodite kollineaarsuse probleemi ületamisele.

Mõningate arvamuste kohaselt uute toodete turuletoomise madal edumäär toidutööstuses on osaliselt tingitud jätkuvast korporatiivsest eksiarusaamast, et toitumiseelistused muutuvad aeglaselt, ja et tarbijatele on vastumeelne ülemäära uudne toidukaup (Galizzi ja Venturini, 1996). Prescott et al (2002) märgivad vastupidiselt, et tarbijate toitumise eelistused on pidevas muutuses. Dissertatsiooni Uuringu II kui ka dissertandi varasemate pikaajaliste uuringute tulemused kinnitavad Prescott et al (2002) tulemusi. Lisaks, uuring kinnitas samuti Grunert et al (1996), Moskowitz et al (2005) ja Rabino et al (2007) järeldusi, et tarbijad erinevad märgatavalt oma toidueelistustes (vt näiteks, Uuringu II tulemused mustripõhisest segmenteerimisest). Nende tulemuste rakenduslikuks väljundiks on kokkuvõte, et korporatsioonid on sunnitud proaktiivsemalt oma tooteid uuendama, et olla konkurentsivõimelised, kinnitades seega ühtlasi Grunert et al. (1996) ning Trail ja Grunert (1997) vaateid. See on eriti tähtis sellistes küpsusfaasis majandusvaldkondades nagu tarbe- ja toidukaupade tootmine.

Järeldused

Järeldus 1: Eelistusanalüüsi eksperimendi kavandamisel põhinevat metoodikat kasutatakse tootearenduses sageli, et paremini mõista tarbijaeelistusi. Seni kasutatavad eelitusanalüüsi metoodikad võimaldavad testida piiratud arvu eelvalitud elementide (tooteomaduste) kombinatsioonide võimalikke interaktsioone. Praktikas vajatakse täiustatud tootearenduse meetodit, mis tuvastaks nii üksikud kui ka kõik ilmutatud interaktsioonid. Tootearendus-metoodika täiustamise täiendavaks võimaluseks on varjatud interaktsioonide analüüs – „mis-siis-kui“ analüüsid võimaldavad arendajal tuvastada uuritavate toodete omaduste toimimist sõltuvuses teistest elementidest.

Senikasutatavate metoodikate puuduseks on kasulikkuse skoori suhteline väärtus eelistusanalüüsis, mis piirab toodete omavahelist võrdlust, tooteinformatsiooni kogumist ja taaskasutatavust. Nende piirangute ületamine võimaldab täiustada tootearendusprotsessi, iseäranis turunduse mõistes küpsusfaasis toodete klassis.

Järeldus 2: Eksperimendi kavand on võtmeks elementide (tooteomaduste) vaheliste interaktsioonide tuvastamisel eelistusanalüüsis. Dissertatsioonis pakutav meetod põhineb isomorfsetel permuteeritud eksperimendi kavanditel (IPEKidel). Vastavalt pakutavale mudelile IPEK-id kasutavad märgitud eksperimendi kavandeid atribuutide ja elementide permutatsiooniks. IPEK meetod võimaldab luua hulgi unikaalseid (ehkki statistiliselt isomorfseid) kavandeid. Selle kasutus eelistusanalüüsis tekitab hulgi ühtlaselt jaotatud kõikvõimalikke paari-kaupa elementide (tooteomaduste) kombinatsioone võimaldades tuvastada üksikuid ja ühtlasi ka kõiki omavahelisi paaris-interaktsioone. Lisaks, IPEK, põhinedes individuaalsetel kasulikkuse mudelitel, võimaldab tuvastada kliendieelistuste põhist latentset segmentatsiooni, mille skooride väärtused on absoluutsuurused (tuleneb IPEK-ist). Meetod on üldistatav elementidevahelistele kolmandat ja kõrgemat järku interaktsioonidele. Näiteks, Uuringute I ja III empiirilises osas kasutatakse 400 taolist IPEK-i.

Järeldus 3: IPEK-i rakendusel põhinev metoodika avab nii üksikud kui ka kõik paarikaupa interaktsioonid elementide (tooteomaduste) vahel eelistusanalüüsi kontekstis. Uuuringu I empiirilised tulemused kinnitavad seda käsitlust. Uuring analüüsib tuvastatud interaktsioone apelsinijoogi (andmestik I) ja küpsiste (andmestik II) tooteomaduste vahel. Enamiku uuritud juhtumite puhul ainult väike osa interaktsioonidest on olulised: 216 elemendipaari hulgast apelsinijoogi uuringus ja potentsiaalse 540 elemendipaari hulgast küpsiste puhul Uuringus I vastavalt ainult 5 % ja

3 % olid olulised. Olulised ilmutatud interaktsioonid võivad lisada kasulikkust 10 kuni 30 punkti (vastab tingimusliku tõenäosuse kasvule ligikaudu 10–30 %, et klient on huvitatud toote ostmisest) või vähendada seda samal määral, kui kombinatsioon osutub pärssivaks. Uuring näitas samuti, et ilmutamata interaktsioonide analüüs (stsenaariumid) tootearenduseks tekitab 'mis siis kui' tüüpi stsenaariumid omaduste asendatavuse (näiteks, tulenevalt tehnoloogilistest või majanduslikest piirangutest) mõjust ennustatavatele kliendieelistustele.

Järeldus 4: Töös uuritakse autori poolt pakutavat uut metoodilist lähenemist kliendikesksele eksperimendi kavandamisel põhinevale tootearendusele, mis on autori enda või tema osavõtul läbiviidud sadade empiiriliste uuringuprojektide analüüsi tulemus. Dissertatsioonis pakutakse välja eelistusanalüüsi metoodikat täiendav ja edasi arendav Reegleid Kujundava Eksperimenteerimise (RKE) protsess koosnevana kuuest sammust: 1) Sisendandmete ettevalmistamine (elemendid: toote omadused ja sõnum); 2) Testkontseptsioonide (eksperimentaalselt kavandatud kontseptsioonid) loomine kasutades IPEK-it; 3) Andmete kogumine klientidelt (näit., eksperimentaalselt kujundatud kontseptsioon-toodete ostmise kavatsus); 4) Tulemuste analüüs / interaktsioonid, sh. kõigi interaktsioonide tuvastamine (ilmutatud ja ilmutamata); 5) Mustripõhiste latentsete segmentide identifitseerimine; 6) Genereeritud reeglite rakendamine uute toodete ja teenuste loomiseks (reeglid – kvantitatiivsed suhted tooteomaduste vahel). Sammud 1–4 on autori poolt täiustatud eelistusanalüüsi metodoodikast lähtudes. Tooteuuendusvõimaluste tuvastamisel lähtutakse testis osalejate segmenteerimisest samameelsete indiviidide klastritesse (erinevate kasutusmustritega), mille täppisseadistus põhineb avastatud (toote)omaduste interaktsioonidel. Uuring II demonstreerib RKE protsessi rakendatavust jäätise (toote)omaduste kliendieelistuste uuringu näitel.

Järeldus 5: Kliendieelistustest lähtuv oluliste tootetunnuste süsteemne rekombineerimine (kombinatoorika või kombinatoorne innovatsioon), mida uuritakse dissertatsioonis, on toidukaupade arendamises rakendatav eelkõige kui küpsusfaasis toodete uuendusprotsessi lähtesamm. Innovatsioonivõimaluste identifitseerimine kasvab välja osalevate indiviidide mustripõhisest segmenteerimisest. Uuring näitas, et kliendieelistuste ennustatavus on kõrgeim sihtrühmas 2 ('Tervise otsijad'). Pakutav metoodika loob teoreetilise aluse võimalikuks meetodi laiendamiseks tulevikus, rakendades 'veebi otsingumootori' põhist sisendmaterjali automaatse kogumise ja sisu analüüsi.

Järeldus 6: Dissertatsiooni uuringute tulemusi kasutatakse toote omaduste ja sõnumi kliendieelistuste struktuurse ja taaskasutatava informatsiooni kogumiseks ning rakendamiseks tootearenduses. Kasutades RKE metoodikat, analüüsitakse tootearenduse suunitlusega andmebaasi aluseid (Uuring II). Andmebaas sisaldab infot kontseptsiooni ja maitse tasanditest. Tehakse ettepanekud kaheosalise andmebaasi kujundamiseks. Esimene osa sisaldab tootekontseptsioonide, mis sisaldavad mõlemaid – tunnuseid ja emotsioone, süsteemset analüüsi. Teise osa moodustab toodete konkurentsiraamistik kui lähtesisend süsteemseks tootearenduseks. Selles osas tuvastatakse oodatava ja mõistliku toote- ja maitseomaduste vahemikud, tüüpiliste toodete heakskiidu tase, seosed meeldimise ja maitseomaduste vahel ning toimub maitseeelistuste segmenteerimine.

Andmebaasi praktiline kujundamine on kajastatud Uuring II empiirilises osas. Uuring kirjeldab andmebaasi Crave It!™ Foundational Database 30 süsteemselt uuritud tootega. Uuring tuvastas kolm mustripõhist tarbija segmenti: 'Viimistle', 'Klassikaline' ja 'Fantaseerija'. 'Klassikalise' segmendi kõrge kasutusmääraga elemendid loovad kõrgema ennustatavusega kliendieelistusi kui 'Viimistle' segment. See näitab, et kliendieelistuste mõistmine läbi mustritepõhise segmenteerimise loob eeldused paremini eesmärgistatud tootearenduseks.

Töö praktiline tähtsus

Eksperimenteerimisel on äärmiselt suur tähtsus tootearenduse igas valdkonnas, mis sõltub kliendieelistustest. Töös pakutakse välja süstematiseeritud ja struktureeritud eksperimenteerimise meetod RKE selgitamaks kliendi vajadusi ja eelistusi isegi siis, kui kliendid ise ei suuda neid sõnastada, tehes seega tootearenduse sihipärasemaks ja kliendile orienteeritumaks. Selle tulemusena kasvab ettevõtete võime lihtsustada tootearendusprotsessi, mis põhineb usaldusväärsel kliendiinfol, on konkurentsivõimeline ja annab planeeritud tulemusi.

Uuritud metoodika testib rohkearvulisi tootekontseptsioone elementide unikaalsete kombinatsioonidena individuaalsel alusel lihtsustades ennustatavat kliendieelistuse infot võrreldes traditsiooniliste meetoditega, mis hindavad piiratud arvu eel-valitud kontseptsioone või kasutavad ühte eksperimendi kava igale testis osalejale. Tulemuseks on paremad tooted ja edukam toodete turuletoomine. Kliendi andmestiku praktilist väärtust tõstavad IPEK-id, mis lihtsustavad tooteomaduste vaheliste interaktsioonide avastamist võimaldades luua tooteid, mis on kliendile paremini vastuvõetavad. Lisaks, ilmutamata interaktsioonid võimaldavad 'mis siis kui' stsenaariume, et analüüsida toodete asendusomaduste kasulikkuse skoori mõju ennustatavale kliendieelistusele. See lubab tootearendajal leida praktilisi kompromisse enamiku majanduslikult ja tehnoloogiliselt vastuvõetavate omaduste ja kliendieelistuste vahel.

Pakutav modifitseeritud eelistusanalüüs koos aluseks oleva isomorfse permuteeritud eksperimendi kavandamisega lihtsustab latentsete kliendivajaduste ja soovide avastamist, mida kliendid ise võivad mitte tuvastada ja/või sõnastada tootearenduses kasutataval kujul. Tulemusena, mustritepõhine segmenteerimine ja nii üksiku kui kõigi interaktsioonide tuvastamine viib reeglistiku kujundamiseni (kvantitatiivsed suhted tooteomaduste vahel), mis teeb tooted või teenused fokuseeritumaks ja konkurentsivõimelisemaks.

Struktureeritud eksperimenteerimise meetod lihtsustab ideede formuleerimist tootearenduses luues produktiivse probleemilahendamise keskkonna.

RKE projektide jaoks elementide ettevalmistamine soodustab nende kategoriseerimist erinevatesse atribuutidesse lihtsustades mõjusamate ideede genereerimist. See annab samuti panuse korporatiivsesse tootearenduse ideeloomesse, mille tulemusi muidu häälekamad või tähtsamal positsioonil olevad isikud võivad kallutada. RKE jätab ära hindamise faasi idee genereerimisel ja delegeerib selle funktsiooni klientidele lihtsustades vabamat ideeloomet. Korporatiivsete osavõtjate ülesandeks saab mitte leida 'häid' tooteomadusi vaid ennemini genereerida laia skaalat erinevaid tootemaduste ideid, mida hinnatakse klientide poolt. See kehtib samuti fookusgruppidele, mis on muidu tugevasti sõltuvad moderaatorite kvalifikatsioonist ja objektiivsusest.

Üks tähtsamaid praktilisi RKE eeliseid on teadmuse jagamise lihtsustamine ja soodustamine. Selle statistiline alus võimaldab andmete kogumist, võrdlemist ja muundamist tegusaks teadmuseks lahendite mõõdetavuse ja RKE struktureeritud olemuse tõttu. Lisaks, üldistatud lähenemisviis teeb kliendiandmestiku interpreteerimise paremini arusaadavaks korporatsioonide allüksuste ja juhtimistasandite vahel – alates T&A-st, tootearendusesest kuni turunduse ja juhtimiseni. Struktureeritud lähenemisviis võimaldab luua üldkasutatavaid instrumente (näit., Ideamap.NET), mida saab kasutada laias ärivajaduste spektris, mitte ainult UTAs ja toote sõnumi arenduses. Unifitseeritud metoodika ja instrumendid omavahel teevad lihtsamaks korporatsiooni personali koolituse ja teadmiste levitamise.

Uuritud RKE meetodid on maailmas laialdaselt aktsepteeritud kui praktiline viis kliendikesksuse kasvatamiseks uue toote ja selle sõnumi arenduses. Paljud globaalsed korporatsioonid on saanud kasu selle meetodi rakendusest. Seda on kasutatud tooteomaduste, maitse, pakendi ja sõnumi arendamiseks UTA käigus sellistes kompaniides nagu *Coca Cola*, *Campbell's*, *McDonalds*, *Nestle*, *Pepsi*, *Kraft*, *Dunkin' Donuts*, *Lipton*, *Tetley*, *Heineken*, *Dannon* ja *m&m* kliendipõhise tootearenduse varastes faasides. Seda on kasutatud (litsenseeritud) *Hewlett Packard* tootearenduse, turunduse, promotsiooni ja hinnakujunduse tarbeks; litsenseeritud kompaniile *MasterCard* uute krediitkaardite pakkumiseks; globaalselt on kasutanud teiste hulgas *Unilever*, *P&G*, *Microsoft*, *Ford*, *American Express* ja *Johnson and Johnson*.

Teoreetiline panus

Käesolev töö annab panuse eelistusanalüüsi metoodikasse tuues sisse uudsed lähenemisviisid erinevate tooteomaduste omavaheliste interaktsioonide avastamisse ja määramisse tootearenduses. Seni kasutusel olnud meetodid kas ignoreerisid või testisid ainult väikest osa neist interaktsioonidest. Teadmine sünergiast, kus tunnuste netoefekt on palju suurem, kui võiks eeldada üksikute toimete summast, on võimalus saavutada kõrgemat kliendi rahulolu pannes need sünergilised elemendid kokku. Samuti vastupidises situatsioonis, kui kaks kombinatsiooni elementi toimivad omavahel pärssivalt, siis eelnev teadmine sellest negatiivsest efektist annab tootearendajale võimaluse vältida omaduste pärssiva kombinatsiooni kasutamist tootes.

Lisaks, dissertatsioon annab panuse eksperimendi kavandamisse uurides ja arendades edasi individuaalse isomorfse eksperimendi kavandamise metoodikat. Moskowitzi (1994) algse ettepaneku sellesuunalist kasutamist varem takistas uuringute ja üldistatud metoodika puudumine. Töös tutvustatakse nii kontseptuaalset kui matemaatilist mudelit, millega see takistus ületatatakse.

Eksperimenteerimise metoodika täiendamisega alusteooria ja eristavate sammudega kliendikeskses küpsusfaasis toodete arendamises antakse panus kliendieelistuste teooriasse tõestades protseduure ja seoseid (RKE), mis võimaldavad süstematiseerida teadmisi kliendieelistustest. Tänu RKE poolt võimaldatava individuaalsete eksperimendi kavandite permuteeritud iseloomule, saab erinevates projektides kogutud teadmust omavahel ühendada, võrrelda ning kasutada tulevikus toimuvateks uuringuteks ja tootearenduseks, mis polnud realiseeritav struktureerimata või traditsioonilise eksperimenteerimisviisidega kavandamistel. Oma uuringute tulemusena, autor oli üheks uue teadusvaldkonna, mida tuntakse MindGenomics™ (Moskowitz, Gofman, Beckley ja Ashman, 2006; Gofman ja Moskowitz, 2008) nime all, tutvustajaks. MindGenomics™, ühendades genoomika mudelid ja informaatika tehnoloogia, loob süsteemse arusaamise, kuidas inimesed reageerivad ideedele kasutades RKE-d paljude testidega tuvastamaks eelistuste mustreid (genoomika põhine muster). See lähenemisviis võib olla aluseks süsteemsele struktureeritud kliendipõhisele tootearendusele teistes valdkondades.

Piirangud ja soovitused edasisteks uuringuteks

Uuringud I-III piirdusid väikeste ja keskmise suurusega projektidega. Üheks võtmeaspektiks dissertatsiooni lähenemisviisis on võime kombineerida paljude testiosaliste andmeid üheks andmekogumiks võimaldamaks testida paljusid elemente ja interaktsioone. Kuues atribuudis, millest igaüks sisaldab kuut elementi, saame määramiseks 540 paari-kaupa interaktsiooniefekti (muutujad). Peamiseks tehniliseks takistuseks selle lähenemisviisi rakenduses suurematele andmehulkadele on olnud regressiooni andmetöötlusvara, mis pole enam probleemiks kaasaegse tehnoloogia rakendamisel.

Interaktsioonide avastamise ja määramisega seotud probleemid tulevasteks uuringuteks:

- Käesolevas dissertatsioonis jõuti peamiselt ainult teist järku interaktsioonide praktiliste rakendusteni. Välja töötatud põhialuseid võiks rakendada avastamaks kõrgemat järku interaktsioone rahuldava hulga eksperimendi kavandite permutatsioonidega. Kõrgemat järku interaktsioonide metoodika nõuab täiendavaid uuringuid.
- Kontseptsiooni optimiseerimise ülesande lahendamine hõlmates paari-kaupa ja võimalik, et ka kõrgemat järku interaktsioone.

- Üks jätkuvaid teemasid on uurida interaktsioone ’miks’. Võidakse küsida, miks teatavad kombinatsioonid töötavad ebaharilikult hästi või ebaharilikult halvasti. Kas see on lihtsalt statistiline kõrvalekalle? Kas interaktsioonid on korratavad? Neile küsimustele ei saa veel vastata ja see on tulevaste uuringute teema.

Töö (Uuringud II ja III) näitas vajadust struktureeritud andmebaasi kui ’käsiraamatu’ ja ’innovatsioonimasina’ järele tootearenduses. Edasiseseks uurimisküsimuseks on informatsioon, mida hõlmatakse sellisesse andmebaasi.

Uuringus III käsitletud kombinatoorne innovatsioon loob aluse arenevateks rakendusteks sisendandmestiku automaatsel kogumisel ja klassifitseerimisel veebi otsingumootori abil (Chau, Zeng ja Chen, 2001) ning sisu analüüsil (Krippendorff, 2004). See omakorda loob aluse süsteemseks RKE-rakendusega kliendieelistuste info poolautomaatse kogumise protsessiks.

MÕISTETE SELGITUS (KASUTATAVANA TOOTEARENDUSES)

Adaptiivne eksperimenteerimine – meetod manipulatiivsete katsete eetiliseks läbiviimiseks inim-dominantsetes ökosüsteemides.

Atribuut (samuti *muutuja*, *silo* või *kategooria*) – grupp seotud komponente eelistusanalüüsis – sarnased elemendid, millest koostatakse tootekontseptsioonid (kontseptuaalsed prototüübid). Atribuudid on näiteks: “Maitsed” (võimalikud elemendid näiteks: “Apelsinimaitseline”, “Šokolaadimaitseline”, “Maasikamaitseline”); “Rasvasisaldus” (võimalikud elemendid: “Rasvavaba”, “Madala rasvasisaldusega”). Ainult üks element saab olla korraga valitud eelistusanalüüsi atribuudiks. Atribuudid eelistusanalüüsis on vastavuses eksperimendi kavandi *muutujatega* (mõisteid kasutatakse vahel võrdväärsetena).

Eelistusanalüüs (eestikeelses kirjanduses ka *eeliskombinatsiooni analüüs* või *meetod*, *koondanalüüs*) – statistiline turu-uuringu tehnika, mis selgitab kuidas inimesed väärtustavad erinevaid omadusi, millest individuaalne toode või teenus koosneb. Eelistusnalüüsis palutakse osalejatel langetada rida valikuid. Nende valikute analüüs selgitab välja erinevate elementide kasulikkuse (tähtsuse) heaolu või mõju suhtes.

Eksperimendi kavand (testdisain) – kontseptsiooni elementide kombinatsioonide eksperimenteerimise (testimise) statistiline plaan. See on eelistusanalüüsi ja eksperimendipõhiste meetodite aluseks.

Eksperimenteerimine (*struktureeritud* ja *struktureerimata*) on testdisaini proovimine, mille käigus tehakse kindlaks, kui hästi erinevad asjad (näiteks, kontseptsioonid või elemendid) toimivad. *Struktureeritud* eksperimenteerimine põhineb testi disaini muutmisel, *struktureerimata* eksperimenteerimine on enamuses juhuslik ja põhineb eelistuste kujunemisel.

Element – kontseptsiooni koostisosa eelistusanalüüsis. Elemendiks võib olla omadus, sõnum või muu tarbija testimise komponent, mis üheskoos kombineerituna moodustavad kontseptsiooni. Element on lühike täpne kirjeldav lause või muu tähenduse kandja, mis loob individualiseeritud tooteelemendid grupeerituna sarnaste omaduste atribuutidesse. Elemendid on näiteks: "Pakendatud suletud metallpurki"; "Tumeda šokolaadi tükkidega"; "Madala rasvasisaldusega". Elemendid eelistusanalüüsis on vastavuses eksperimendi kavandi *tasemetega* (mõisteid kasutatakse vahel võrdväärsetena).

Interaktsioon esineb kui kahe atribuudi kombineeritud mõju erineb nende kasulikkuse skooride summast. *Ilmutatud interaktsioonid* on elementide paarid, mille kombinatsioon kutsub esile statistiliselt olulise muutuse regressioonvõrrandis või variatsioonanalüüsis. Ilmutatud interaktsioonid, millede kombineeritud efekt on suurem kui atribuutide kasulikkuse skooride summa, nimetatakse sünergismiks (positiivne interaktsioon). Pärsingud on interaktsioonid, mis põhjustavad väiksema kombineeritud efekti kui on nende kasulikkuse skooride kogusumma. *Varjatud (ilmutamata) interaktsioonid* – interaktsiooni vaadeldakse kui tingimuste mõju mõnedele sõltuvatele muutujatele (näiteks, uuritavate toodete omaduste esinemine sõltuvuses teistest elementidest).

Isomorfne Permuteeritud Eksperimendi Kavand (IPEK, või ka *Isomorfne Permuteeritud Testdisain*) permuteerib testi disaini nii, et igale individuaalsele testis osalejale näidatakse mitut erinevat kombinatsiooni. Testdisaini permuteerimine loob isomorfsed disainid, mis on üksteise suhtes statistiliselt võrdsed.

Järk (interaktsioonil, vastasmõjul) – elementide arv, mille vastatikust mõju uuritakse. Paari puhul on järk 2, kolme elemendi puhul on järguks 3 jne.

Kasulikkuse skoor (samuti *kasulikkuse väärtus*, *mõju* või *osaväärtus*) – elemendi tunnetatav väärtus, samuti tarbija arusaamade ja eelistuste tundlikkus tooteelementide muutmise suhtes. Kasulikkuse *absoluutsed* väärtused (skoorid) on võrreldavad erinevate atribuutide ja projektide vahel. Kasulikkuse *suhtelised* väärtused on võrreldavad ainult selles kontekstis, kuhu atribuut kuulub. Näiteks, kui element 'Rasvavaba' atribuudist 'Rasvasisaldus' kasulikkusse skoor on +10 ning teisel elemendil 'Šokolaadimaitseline' atribuudist 'Maitsed' skoor on +20, siis eelistusanalüüsis absoluutväärtuste põhjal saab uurija teha järelduse, et 'Šokolaadimaitseline' toode suurendab tarbija ostu tõenäosust 20%, kui 'Rasvavaba' suurendab seda tõenäosust ainult 10%. Suhtelistel väärtustel põhinevas eelistusanalüüsis ei saa neid skoore otseselt võrrelda, kuna neil on tähendus ainult oma atribuudis sisalduvate elementide suhtes.

Kombinatoorne innovatsioon – uue loomise või vana ümber-organiseerimise protsess uuel viisil või vormis. UTA kontekstis kombinatoorne innovatsioon on uurimis- ja arendustegevuse oluliste osade süsteemne rekombineerimine.

Kontseptsioon (*prototüüp*, *kontseptuaalne prototüüp*) – testitavate elementide kombinatsioon eksperimendi kavandis. See on tekstiline ja/või graafiline uue toote kirjeldus. Eelistusanalüüsis on kontseptsioonideks elementide kombinatsioonid (tooteomadused või – kirjeldus). Tüüpiline kontseptsioon eelistusanalüüsis sisaldab 3 kuni 7 elementi, mis kokku kirjeldavad toodet. Testis osalejad hindavad erinevaid kontseptsioone testdisaini põhjal ja annavad hinde ühele või mitmele hinnatavale küsimusele (näit., ostusoov, huvi).

Kontseptsiooni testimine – protsess, milles kasutades nii kvalitatiivseid kui kvantitatiivseid meetodeid hinnatakse tarbijate reageeringut tooteideele (kontseptsioonile) enne toote turule viimist.

Lisandkonstant (lõpetamata kontseptsioonidega eelistusanalüüsis) **–** testis osalejate baashuvi uue toote vastu (ilma ühegi elemendita).

Mustripõhine latentne segmenteerimine (*RKE segmenteerimine*, *Seaduspärasusel põhinev vaiksegmenteerimine*) on tarbjate segmenteerimise protsess, mille käigus tarbijad grupeeritakse kontseptsioonidele reageerimise põhjal, sõltumata nende demograafilistest andmetest.

Optimiseerimine (turunduses) – tarbijaeelistuse parendamise protsess, või toote/idee/sõnumi/pakendi osade muutmine, et seda tarbijatele ahvatlevamaks muuta.

Reegleid Kujundav Eksperimenteerimine (*RKE*, *Reglementeeriv eksperimenteerimine*) **–** süstematiseeritud lahendusele orienteeritud eksperimenteerimise äriprotsess, mis disainib, testib ja muudab alternatiivseid ideid, pakendeid, tooteid või teenuseid reeglipärasel viisil testdisaini raames nii, et arendaja ja turundaja avastavad reegleid ja seaduspärasusi, mis näitavad tarbijaeelistuste kujunemist, isegi kui tarbija ei suuda vajadust artikuleerida, lahendusest rääkimata.

RKE reeglid – kvantitatiivsed seosed RKE ja tarbijaeelistuste elementide vahel, samuti juhised tarbijaeelistuse (ostusoovi) suurendamiseks erinevates stsenaariumites. RKE suunab disainerit ja turundajat eesmärke saavutama. RKE kirjeldab tarbijale kõige tõenäolisemalt meeldivamaid ideede (omadused, sõnumid) kombinatsioone.

Tarbijaeelistus – reaalne või kujuteldav valik alternatiivide vahel ja võimalus alternatiivide järjestamiseks õnne, rahulolu, tänutunde, naudingu ja saadava heaolu (kasulikkuse) põhjal.

Testis osaleja – inimene kellelt palutakse mingit suulist või kirjalikku infot uuringu ajal.

Täieliku kontseptsiooni meetod – iga atribuut on esindatud igas kontseptsioonis. Täiskontseptsioonil põhinev eelistusanalüüs hindab kasulikkuse suhtelisi väärtusi, mida ei saa võrrelda atribuutide ja projektide vahel.

CURRICULUM VITAE

Personal details

Name Alexander Gofman

Born January 1, 1959 in Artyomovsk, Donetsk Region, Ukraine.

Citizenship USA

Home 26 Amalfi Dr.,
Cortlandt Manor, NY 10567, USA
e-mail: axg@alexgofman.com

Current Positions

Vice President, Moskowitz Jacobs Inc.
Platinum Mile,
1025 Westchester Ave.,
Moskowitz Jacobs Inc.,
White Plains, NY 10604
USA
Ph:+1-914-421-7404
E: agofman@mji-designlab.com

Adj. Associate Professor, Pace University
Lubin Business School,
White Plains Graduate Center,
1 Martine Avenue,
White Plains, NY 10606
USA
E: agofman@pace.edu

Education **Makeevka Mining Safety Institute (MakNII Aspirantura)** ***1986–1991***
Completed all courses and passed all candidate exams specializing in SW and HW development for mining geophysics

Donetsk Polytechnic Institute[3] ***1976–1981***
MS in Computer Science with Honors
(*Summa Cum Laude* – top of the class)

High School #24, Artyomovsk, Ukraine (Graduated in 1976 with *Gold Medal*)

Language skills English, Russian, Ukrainian, Spanish (basic)

[3] Now Donetsk National Technical University

Employment History

Pace University **2007–Present**
Adj. Associate Professor of Marketing
Taught graduate classes in NPD (MAR 660), Business (MGT 682) and Marketing (MAR 635) Research. In addition, delivered lectures as a guest professor for various classes and continuing education courses at University of Pennsylvania (Wharton Business School), NYU (Stern School of Business) and UiTM (MARA) in Malaysia.

Moskowitz Jacobs Inc. White Plains, NY **1992–Present**
Vice President *(1996–present)*
Director *(1994–1996)*
Department Manager *(1992–1994)*
One of primary leadership force of this award winning company established by a world-renowned scientist Dr. Howard Moskowitz and globally recognized for excellence and innovation in consulting, brand developing, marketing and media research, providing advanced tools, portals and consulting to global clients such as HP, Citi, Microsoft, J. Walter Thompson, Young & Rubicam, P&G, Unilever, MasterCard, Pfizer, Merck, Novartis, Prudential, Amex, GE, Ford, AT&T, J&J, Time Life, Coca Cola among many others.

OKNA Corp., Lyndhurst, NJ **1991–1992**
Senior Software Developer
As a part of the team, developed the first PIM for Windows on the market; the software has been highly rated by the leading tech magazines in the USA.

Donetsk Polytechnic Institute[4], Donetsk (Ukraine) **1988–1990**
Adjunct Instructor

State Mining Geophysics Research Institute (Ukraine) **1984–1991**
Senior Research Fellow *(1989–1991)*
Research Fellow *(1987–1989)*
Junior Research Fellow *(1984–1987)*
The head of international group of SW/HW developers. The group was noted as one of the most advanced in the Eastern Europe (many of the group members now hold top positions in some of the well-known American and Canadian technology companies).

Geophysics Computational Center, Ukraine **1981–1984**
Systems Engineer

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4 Now Donetsk National Technical University

CURRICULUM VITAE

Nimi:	Alexander Gofman
Sünniaeg ja -koht:	1. jaanuar 1959, Artjomovsk, Donetski oblast, Ukraina
Kodakondsus:	USA
Aadress:	26 Amalfi Dr., Cortlandt Manor, NY 10567, USA e-mail: axg@alexgofman.com

Töökoht, amet:	**Asepresident, Moskowitz Jacobs Inc.** Platinum Mile, *1025 Westchester Ave.,* *Moskowitz Jacobs Inc.,* *White Plains, NY 10604* *USA* *Ph:+1-914-421-7404* *E: agofman@mji-designlab.com*	**Adjunkt dotsent, Pace Ülikool** Lubini Ärikool, *White Plains Graduate Center,* *1 Martine Avenue,* *White Plains, NY 10606* *USA* *E: agofman@pace.edu*

Haridus:	**Makejevka Kaevandusohutuse Instituut (MakNII) aspirantuur** ***1986–1991*** Läbinud täieliku õppekava ja sooritanud kandidaadieksamid kaevanduse geofüüsika tarkvara ja riistvara arenduses **Donetski Polütehniline Instituut**[5] ***1976–1981*** Magister arvutiteaduses, *Summa Cum Laude* **Keskkool Nr 24**, Artjomovsk, Ukraina (kuldmedal 1976)
Keelteoskus:	Inglise, vene ja ukraina keel, algtasemel: hispaania keel

[5] Praegu Donetski Riiklik Tehnikaülikool

Teenistuskäik

Pace Ülikool **2007–praeguseni**
Adjunkt dotsent turunduses
Õpetanud magistrikursusi Tootearendus (MAR 660), Äri (MGM 682) ja Turundus-uuringud (MAR 635). Lisaks olnud külalislektor erinevatel kursustel ja täiendkoolituses Pennsylvania Ülikoolis (Whartoni Ärikool), NYU (Sterni Ärikool) ja UiTM (MARA) Malaisias.

Moskowitz Jacobs Inc. White Plains, NY **1992–praeguseni**
Asepresident *(1996–praeguseni)*
Direktor *(1994–1996)*
Osakonna juhataja *(1992–1994)*
Dr. Howard Moskowitz'i asutatud konsultatsioonifirma, valdkonnad: turundus- ja meediauuringud. Suuremad kliendid: HP, Citi, Microsoft, J. Walter Thompson, Young & Rubicam, P&G, Unilever, MasterCard, Pfizer, Merck, Novartis, Prudential, Amex, GE, Ford, AT&T, Time Life, Coca Cola jpt.

OKNA Corp., Lyndhurst, NJ **1991–1992**
Vanem tarkvaraarendaja
Meeskonna liikmena osalenud esimese PIM for Windows turuletoomises; tarkvara sai kõrge hinnangu USA tehnoloogiaajakirjades.

Donetski Polütehniline Instituut[6], Donetsk (Ukraina) **1988–1990**
Õppeülesannete täitja

Riiklik Kaevanduse Geofüüsika Uurimisinstituut (Ukraina) **1984–1991**
Vanemteadur *(1989–1991)*
Teadur *(1987–1989)*
Nooremteadur *(1984–1987)*
Rahvusvahelise tark- ja riistvaraarenduse töögrupi juht. Grupp leidis äramärkimist ühena Ida-Euroopa parimatest (paljud grupi liikmed on praeguseks tipp-positsioonidel USA ja Kanada tehnoloogiafirmades).

Geofüüsika Arvutuskeskus, Ukraina **1981–1984**

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6 Praegu Donetski Riiklik Tehnikaülikool

DISSERTATIONES RERUM OECONOMICARUM UNIVERSITATIS TARTUENSIS

1. **Олев Раю.** Экономическая ответственность и ее использование в хозяйственном механизме. Tartu, 1994. Kaitstud 20.05.1991.
2. **Janno Reiljan.** Majanduslike otsuste analüütiline alus (teooria, metodoloogia, metoodika ja meetodid). Tartu, 1994. Kaitstud 18.06.1991.
3. **Robert W. McGee.** The theory and practice of public finance: some lessons from the USA experience with advice for former socialist countries. Tartu, 1994. Kaitstud 21.06.1994.
4. **Maaja Vadi.** Organisatsioonikultuur ja väärtused ning nende vahelised seosed (Eesti näitel). Tartu, 2000. Kaitstud 08.06.2000.
5. **Raul Eamets.** Reallocation of labour during transition disequilibrium and policy issues: The case of Estonia. Tartu, 2001. Kaitstud 27.06.2001.
6. **Kaia Philips.** The changes in valuation of human capital during the transition process in Estonia. Tartu, 2001. Kaitstud 10.01.2002.
7. **Tõnu Roolaht.** The internationalization of Estonian companies: an exploratory study of relationship aspects. Tartu, 2002. Kaitstud 18.11.2002.
8. **Tiia Vissak.** The internationalization of foreign-owned enterprises in Estonia: An extended network perspective. Tartu, 2003. Kaitstud 18.06.2003.
9. **Anneli Kaasa.** Sissetulekute ebavõrdsuse mõjurite analüüs struktuurse modelleerimise meetodil. Tartu, 2004. Kaitstud 15.09.2004.
10. **Ruth Alas.** Organisational changes during the transition in Estonia: Major influencing behavioural factors. Tartu, 2004. Kaitstud 22.12.2004.
11. **Ele Reiljan.** Reasons for de-internationalization: An analysis of Estonian manufacturing companies. Tartu, 2004. Kaitstud 25.01.2005.
12. **Janek Uiboupin.** Foreign banks in Central and Eastern European markets: their entry and influence on the banking sector, Tartu, 2005. Kaitstud 29.06.2005.
13. **Jaan Masso.** Labour Reallocation in Transition Countries: Efficiency, Restructuring and Institutions, Tartu, 2005. Kaitstud 7.11.2005.
14. **Katrin Männik.** The Impact of the Autonomy on the Performance in a Multinational Corporation's Subsidary in Transition Countries, Tartu, 2006. Kaitstud 29.03.2006.
15. **Andres Vesilind.** A methodology for earning excess returns in global debt and currency markets with a diversified portfolio of quantitative active investment models, Tartu, 2007. Kaitstud 13.06.2007.
16. **Rebekka Vedina.** The diversity of individual values and its role for organisations in the context of changes, Tartu, 2007. Kaitstud 16.11.2007.
17. **Priit Sander.** Essays on factors influencing financing decisions of companies: risk, corporate control and taxation aspects, Tartu, 2007. Kaitstud 19.12.2007.
18. **Kadri Ukrainski.** Sources of knowledge used in innovation: an example of Estonian wood industries. Tartu, 2008. Kaitstud 22.04.2008.

19. **Kristjan-Olari Leping.** Heterogeneity of human capital and its valuation in the labour market. Tartu, 2008. Kaitstud 14.05.2008.
20. **Kadri Männasoo.** Essays on financial fragility – evidence from the corporate and banking sectors in Central and Eastern Europe. Tartu, 2008. Kaitstud 26.05.2008.
21. **Made Torokoff.** Patterns of learning organisation – Estonian experiences. Tartu, 2008. Kaitstud 30.06.2008.
22. **Helena Rozeik.** Changes in ownership structures, their determinants and role in the restructuring of enterprises during transition: evidence from Estonia. Tartu, 2008. Kaitstud 31.10.2008.
23. **Jaanika Meriküll.** Technological change and labour demand. Tartu, 2009. Kaitstud 19.05.2009.
24. **Anne Aidla.** The impact of individual and organisational factors on academic performance in estonian general educational schools. Tartu, 2009. Kaitstud 18.06.2009.