Essays on Information Provision and Information Acquisition in Innovative Settings

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PREFACE

This thesis consists of three essays on information provision and information acquisition in innovative settings. Due to limited resources, decision-makers have to select new ideas and allocate budgets early in the innovation process. Therefore, decision-makers rely on various types of information, such as product and market information, to evaluate new ideas and their potential. While prior research has identified the types of information used in innovation decisions, it remains unclear how the provision of this information and management controls affect decision-makers' information behavior and, consequently, their decision performance. I investigate these issues through a customer feedback study and two experimental studies, using the market information collected in the customer feedback study. I contribute to research and practice by analyzing factors that facilitate decision-making in innovation.

To investigate information provision and information acquisition, I collect market information in the customer feedback study. This allows me to design decision-making experiments with a more realistic setting instead of designing experiments with hypothetical scenarios. Participants in the customer feedback study evaluate several new ideas and indicate their purchase intention for each of them. The purchase intention represents the market potential of the new ideas. This approach has several advantages for the subsequent experiments. First, I can objectively measure decision performance in the experiments based on the market potential of those new ideas selected and budgeted by the participants in the experiment. Second, it allows me to design experiments with economic incentives for the experimental tasks comparable to financial incentives in practice, as participants in the experiments are paid based on the market potential of their selected and budgeted new ideas. Third, obtaining the market potential of new ideas and compensating participants in the experiments accordingly allows me to design decision-making experiments with an economic optimum to analyze how and why behavioral biases cause decision-makers to deviate from this optimum.

In the first essay, I analyze the drivers of customers' purchase intention to test the effects of various influence factors empirically and to obtain market information for the experimental studies. While one line of literature states that customers' impressions of the functional aspects of a new idea influence their purchase intention, another stream argues that the purchase intention depends on how well a new idea solves customers' problems. Based on both streams, I derive ten indicators each for the concepts of product impressions and customer problems. While some product impressions indicators are quantitatively defined by prior research, I translate the largely qualitative concept of customer problems into quantitative indicators. This allows for empirical testing of factors influencing purchase intention based on each stream. In addition, it allows the design of experiments in which participants can acquire both types of market information that provide different customer insights but can be made available on the same scale level for greater experimental control. To generate a pool of new ideas that can be evaluated based on the indicators, I develop app ideas for which I design app presentations. The results of this study reveal that six product impressions indicators (Usefulness, Interest, Design, Benefits, Convenience, Ease of Use) and five customer problems indicators (Degree of Problems, Behavioral Fit, Priority, Improvement, Comparative Gain) drive customers' purchase intentions.

In the second essay, I investigate how the provision of product and market information influences decision performance in idea selection. For innovation, firms either adopt a product-first or market-first approach, which influences the order in which the information is disseminated to decision-makers. Even though the information order differs, prior research shows that both types of information are essential for idea selection and should be provided at some point. However, in dependence on these innovation approaches, the R&D and marketing departments generate and prepare information for reporting with a certain time gap. This raises the question of whether product and market information should be provided to decision-makers as soon as they are available, i.e., with high separation, or combined in one report when both information are available, i.e., with low separation. While providing information at the time of availability keeps decision-makers updated, prior research shows that low information separation can positively influence decision performance. This study offers a more nuanced view by showing that the positive effect of low separation on decision performance depends on the information order. This study shows that while decision performance improves when both types of information are provided with low separation under market-first, this positive effect is weaker under product-first compared to market-first. The reason is that compared to market-first, under product-first, decision-makers have a less immediate need to combine both types of information, reducing the likelihood of information combination even if the separation is low. Consequently, in this study, I show that information separation and information order interactively influence decision performance.

In the third essay, I investigate decision-makers' information processing and acquisition behavior under two control mechanisms: acquisition restrictions and justification. In this experiment, participants acquire information on product impressions and/or customer problems and allocate budget to new ideas. I provide controlled evidence that decision-makers generally prefer information on product impressions over customer problems, even though information on customer problems could be acquired for the same cost. The preference for information on product impressions leads to a negative performance effect when decision-makers can acquire both types of information but are not required to justify their decisions as decision-makers acquire more likely both types of information but process it selectively by ignoring more likely customer problems. This selective attention can lead to a misinterpretation of market potential, particularly in settings where market information is contradicting, for instance, when new ideas score high on product impressions but low on customer problems. However, this study also reveals that justification mitigates selective attention by increasing the likelihood that both types of information are processed. Thus, if firms want to base their innovation decisions on both types of information, justification mechanisms can have a positive impact. I show that when decision-makers have to justify their budget allocation, they are more likely to acquire and process both types of information.

ESSAY 1

Market Information on Product Impressions and Customer Problems

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Abstract

To assess the market potential of new ideas, firms acquire market information in terms of customer feedback. One line of research defines this market information based on product impressions, while another line of research defines it based on customer problems. While information on product impressions informs decision-makers on customers' opinions of functional aspects of new ideas, information on customer problems takes more account of customers' problems and how well new ideas are suited to solve these problems. In this study, I empirically investigate the drivers of customers' purchase intention by examining the effect of product impression indicators and customer problem indicators. For this purpose, I define indicators and respective customer feedback questions based on prior literature. To analyze the effects of these indicators on customers' purchase intention, I create a pool of new ideas by designing 25 app presentations. Participants on Amazon Mechanical Turk rate these apps either on the product impressions or customer problems indicators and indicate their desirability and willingness to pay for each app. The definition of indicators and the creation of app presentations allow me to collect market information for future experiments and to test the effects of the indicators on customers' purchase intentions empirically.

Keywords: market information, purchase intention, product impressions, customer problems

I. Introduction

Evaluating new ideas to select and allocate budget to those with the greatest potential is crucial for firms' long-term success (Cooper 2013; Dziallas 2020; Sukhov et al. 2021; Toubia and Florès 2007). To facilitate the evaluation of new ideas, firms provide decision-makers, such as top management, with various types of information (Cooper 2011; Martinsuo and Poskela 2011; Tzokas, Hultink, and Hart 2004). Thereby, prior research shows that market information is one of the most essential information inputs for evaluating new ideas, as understanding customers, their preferences, and situations is one of the main drivers for innovation success (Adams, Day, and Dougherty 1998; Narver and Slater 1990; Ottum and Moore 1997; Parry and Song 2010; Schmidt, Sarangee, and Montoya 2009).

In terms of market information, it is crucial for firms to understand what drives customers' purchase intentions. Understanding this can help firms design appropriate customer feedback surveys. Additionally, firms can better identify new ideas with the greatest market potential by focusing on those indicators that substantially influence the purchase intention for new ideas (Armstrong, Morwitz, and Kumar 2000; Arts, Frambach, and Bijmolt 2011; Claudy, Garcia, and O'Driscoll 2015; Ulwick and Bettencourt 2008).

One line of literature defines customers' opinions on functional aspects as drivers for customers' purchase intention (hereafter: product impressions; see: Arts, Frambach, and Bijmolt 2011; Candi et al. 2017; Claudy, Garcia, and O'Driscoll 2015; Homburg, Schwemmle, and Kuehnl 2015). Another line of literature states that customer problems and how well new ideas solve these problems are the main drivers (hereafter: customer problems; see: Christensen et al. 2016a; 2016b; Ulwick 2005; Ulwick and Bettencourt 2008). Based on each stream, I determine indicators in this study to empirically analyze their influence on customers' purchase intentions. I investigate the drivers of customers' purchase intention by examining the effects of product impressions indicators and customer problems indicators on purchase intentions.

This is important as, to the best of my knowledge, prior research on product impressions does not cover the concept more holistically by integrating various indicators related to it in one model. Additionally, to my knowledge, no previous research has translated the current qualitative concept of customer problems into quantitative research to empirically investigate how customer problem indicators influence customers' purchase intentions for new ideas.

For the study, I determine ten indicators related to information on product impressions and ten indicators related to information on customer problems. In determining the indicators for product impressions, I rely on previous literature that defines customer feedback in terms of customer opinions on functional aspects of new ideas. For the indicators of customer problems, I draw upon the Jobs-to-be-Done (JtbD) literature, which emphasizes the importance of understanding customer problems and how well a new idea is suited to solve these problems. While previous literature describes this concept mainly qualitatively by outlining the principles and dimensions, I translate the concept into quantitative indicators.

To create a pool of new ideas[1] that can be rated across the indicators, I develop app ideas and design app presentations. The app ideas correspond to one of the following domains: travel, workout, nutrition, friends, and delivery. In each domain, I design five app presentations containing a picture of the app and a description of its features. This results in a total of 25 app presentations. Some app ideas are adaptations of existing apps to which I added further features for additional customer value. Other app ideas are combinations of different app features to create customer value by synergies. Additionally, I design more novel ideas that, to my knowledge, do not currently exist in the app market.

I run the customer feedback study on Amazon Mechanical Turk (MTurk). I used one survey for each domain. Participants can choose the domain of the survey but are randomly assigned to rate the apps either based on product impressions or customer problems indicators.

[1] Some literature uses the term "new ideas" when dealing with the early concept phase and define it as new product or new service when a prototype or market presentation exists. For more consistency in the dissertation and to refer equally to new products and new services, I use "new ideas" even a presentation for customer feedback exists.

Participants rate all five apps of the same domain with the same type of indicator. In addition, they express their desirability and willingness to pay for each app.

To analyze the drivers of customers' purchase intention, I run structural equation models for the product impression concept and the customer problem concept. I run models for the full sample and a subsample that is likely to represent a realistic target group. The target group consists of participants who are highly involved in the respective domain, very open to innovation, and generally willing to pay for an app.

The results reveal that the model fit of both types of information improves by narrowing the full sample to the target group sample. The models of the target group sample show that six product impressions indicators (Usefulness, Interest, Design, Benefits, Convenience, Ease of Use) and five customer problems indicators (Degree of Problems, Behavioral Fit, Priority, Improvement, Comparative Gain) have significant positive influence on *Desirability*, which influences significantly *Purchase Intention*. For product impressions, the indicator Benefits, and for customer problems, the indicator Comparative Gain has the strongest influence. Both target group models show high R^2 (product impressions: 78.71%; customer problems: 81.07%).

I empirically investigate the drivers of customers' purchase intentions based on two streams. I contribute to research by designing a quantitative survey based on the definitions of the concepts of product impressions and customer problems. Even though the customer problems concept is already well defined by prior literature (see: Christensen et al. 2016a; 2016b; Ulwick 2005; Ulwick and Bettencourt 2008), none of this literature determines the concept in terms of quantitative indicators. Translating this concept into quantitative indicators has two main advantages. First, it allows to empirically investigate the effects of the customer problems indicators on customers' purchase intention. Second, it allows designing experiments with information on product impressions and customer problems that provide different customer insights to participants but are made available on the same scale level as both are measured quantitatively on a 7-point Likert scale, which increases experimental control.

By investigating the impact of indicators of product impressions and customer problems on customers' purchase intention, my study is also relevant to practice. Understanding the drivers of purchase intention is crucial as it helps firms better analyze and compare the market potential of new ideas. My study shows that, in general, firms should select participants for customer feedback studies who are highly involved, highly open to innovation, and generally willing to pay, as this increases the accuracy in predicting customers' purchase intention.

Regarding the functional aspects of new ideas, I show that purchase intentions increase if new ideas offer the greatest benefits to customers and are convenient to use. Thereby the new ideas should generate interest and look appealing to draw attention. The new idea should also be perceived as highly useful and easy to use. Regarding customers and their problems, I show that purchase intentions increase when customers frequently experience a problem that is addressed by the new idea. In addition, customers' purchase intentions increase if the new idea effectively solves their problem by improving their situation and if it brings a considerable gain when using it. Thereby, the solution to the problem should be of high priority for customers, and the new idea should fit current customer behavior to be easily integrated.

I contribute to practice by facilitating quantitative market surveys and decision-making in innovations. The concept defined by the JtbD literature helps firms identify unsolved customer problems to develop new ideas. The qualitative questions defined in this literature help to gain detailed insights into the problem and its characteristics. This can be particularly important when a solution is not yet developed, and companies need detailed insights into the problem characteristics. However, qualitative information can be less helpful when comparing already defined ideas for decision-making in innovation. Thus, when top management needs to compare new ideas for idea selection and innovative budget allocation, the more quantitative nature of the defined indicators in this study can support decision-making by increasing the comparability across new ideas.

II. Literature Review

Customers' Purchase Intention

To analyze the market potential of new ideas, firms conduct customer feedback surveys to obtain product evaluations by customers and to predict customers' innovation adoption and purchase intention (Armstrong, Morwitz, and Kumar 2000; Arts, Frambach, and Bijmolt 2011; Claudy, Garcia, and O'Driscoll 2015). Several studies in the field of innovation adoption and purchase intention (see: Arts, Frambach, and Bijmolt 2011; Claudy, Garcia, and O'Driscoll 2015; Hsu and Lin 2015; Ozer 2011; Porter and Donthu 2006; Sun and Zhang 2021; Wu and Wang 2005) are based on the theory of reasoned action (TRA) by Fishbein and Ajzen (1975), and the technology acceptance model (TAM) by Davis (1989).

According to Fishbein and Ajzen's (1975) TRA model, intentions are influenced by individuals' attitudes when making evaluations. In terms of purchase intention, this means that customers consider their attitudes toward a product when evaluating their purchase intention. Based on this TRA concept, Davis (1989) determines the technology acceptance model, which states that perceived usefulness and perceived ease of use influence customers' attitudes toward a new product, which in turn influences their usage intention. Both models and the subsequent studies based on them primarily consider customers' impressions and opinions toward new idea attributes as a driving force for adopting innovations and purchase intention. According to this research, customers assess product features and rate them either more positively or negatively, which influences their purchase intentions (hereafter: product impressions; see: Arts, Frambach, and Bijmolt 2011; Candi et al. 2017; Claudy, Garcia, and O'Driscoll 2015; Homburg, Schwemmle, and Kuehnl 2015).

However, another line of literature states that customers' purchase intention is mainly determined by the problems customers want to solve and how well a new idea solves these problems (hereafter: customer problems; see: Christensen et al. 2016a; 2016b; Ulwick 2005; Ulwick and Bettencourt 2008). This literature states that customers are more likely to purchase new ideas that are best tailored to solve their problems as this creates most value for customers. Consequently, according to this literature, customers' purchase intention is mainly driven by how well a new idea solves their problems rather than by their opinions on its functional aspects (Christensen et al. 2016a; 2016b; Ulwick 2005; Ulwick and Bettencourt 2008).

Feedback on Product Impressions

Information on product impressions gives decision-makers insights into what customers like and dislike about a new idea. It reveals customers' opinions of the functional aspects and their impressions when testing new ideas or learning about its features during product presentations (Arts, Frambach, and Bijmolt 2011; Claudy, Garcia, and O'Driscoll 2015). This type of information is based on models such as TRA and TAM and the following subsequent studies.

Based on the TAM by Davis (1989), Claudy, Garcia, and O'Driscoll (2015) and Sun and Zhang (2021) highlight the importance of developing new ideas that customers perceive as useful and easy to use. According to Thompson, Hamilton, and Rust (2005), firms tend to develop more features than customers perceive as useful because firms perceive that customer value increases the more features are offered. However, this can lead to feature fatigue when customers get overwhelmed by too many features. Thus, it is crucial to understand which features are most useful for customers to avoid too many unnecessary features (Claudy, Garcia, and O'Driscoll 2015; Sun and Zhang 2021; Thompson, Hamilton, and Rust 2005).

Furthermore, studies on product impressions emphasize that in addition to usefulness and ease of use, new ideas should also add emotional value to increase purchase intentions. Emotional value attached to a new idea can improve customers' perception of their future experience by attracting excitement and interest. Thus, the more a new idea adds emotional value by being exciting and interesting, the more likely customers are to desire it, which increases their purchase intention (Chitturi, Raghunathan, and Mahajan 2007; Sun and Zhang 2021).

In addition to emotional value, the perceived functional value plays a crucial role in purchase decisions. When considering a purchase, customers evaluate the price against the value offered by its functions. If the perceived value defined by quality, benefits, and convenience outweighs the price, customers purchase the new idea (Chang and Tseng 2013; Hsu and Lin 2015; Sweeney and Soutar 2001).

Especially for new ideas, the clarity of usage impacts customer evaluations. By ensuring that new ideas are not only easy to use but also clearly explained, firms can enhance customer purchase intentions. The degree to which the usage of new ideas is clearly communicated and understandable affects customers' perception of value and, consequently, their purchase intention (Claudy, Garcia, and O'Driscoll 2015; Mukherjee and Hoyer 2001).

Goode, Dahl, and Moreau (2013) and Homburg, Schwemmle, and Kuehnl (2015) state that the physical appearance of a new idea should support its functionality. According to this research, functionality is defined by consumers' perceptions that a new idea appears to perform well and is capable of doing what it is intended to do. Additionally, the authors state that the design should be appealing to increase customers' purchase intention. They argue that the design is what customers attract first before dealing with its features and functionality. The more appealing a new idea, the more likely customers will evaluate the new idea more positively.

Feedback on Customer Problems

Information on customer problems is based on the literature on the Jobs-to-be-Done concept (see: Christensen et al. 2016a; 2016b; Ulwick 2005; Ulwick and Bettencourt 2008), which focuses on the job customers want to achieve and the problems they face in fulfilling the job. According to this literature, customers buy new ideas to fulfill a specific job, particularly in case they experience problems in fulfilling this job. To generate value, firms should understand the problems customers face to develop feature bundles that solve each component of the problem. Every feature should address one problem component to solve it in the best way possible. Thus, by examining customer problems, firms can ensure that new ideas are tailored to solve customers' problems most effectively. The more the new idea matches the problem, the more likely customers will buy and rebuy it to constantly solve their problems (Christensen et al. 2016a; 2016b; Ulwick 2005; Ulwick and Bettencourt 2008).

Information on customer problems informs decision-makers whether customers face a specific problem, to what extent customers are affected by these problems, and how well a new idea solves these problems. This focus should enable firms to better understand customers' motivations for purchase, not only in terms of the functional but also regarding the emotional and social dimensions of their purchase intent. Firms can understand how and why a new idea will be used for which problem. Thus, information on customer problems is more related to the underlying reasons why customers purchase a specific new ideas instead of understanding customers' impressions of the functional aspects (Christensen et al. 2016a; Ulwick 2005).

Based on the JtBD concept, firms should generate customer value by supporting customers in solving their problems. Therefore, firms must understand whether customers face problems the new idea can address and whether these problems are big enough that customers demand a solution. In addition, firms must understand how well their new ideas solve these problems to select those new ideas that are best tailored to the problems. Consequently, the central questions of this concept relate to the characteristics of customers problems and their solutions. In addition, the questions deal with understanding what matters to customers in solving the problem, whether they are already aware of their problem and already search for a suitable solution, and what they gain when using the new idea to solve a problem (Christensen et al. 2016a; 2016b; Ulwick 2005; Ulwick and Bettencourt 2008).

III. Method

Overview

I run a study on Amazon Mechanical Turk (MTurk) to obtain customer feedback on new app ideas. This allows me to analyze the drivers of purchase intention and to obtain market information for decision-making experiments. For this study, I design customer feedback surveys on product impressions and customer problems by defining ten indicators for each type of information. In addition, I develop app ideas and design app presentations that participants rate across the defined indicators and express their desirability and willingness to pay for each app.

Product information

In order to create a pool of new ideas that can be evaluated based on the indicators, I develop app ideas in the following domains: travel, workout, nutrition, friends, and delivery. In each domain, I develop five apps resulting in a total of 25 apps. For each app I design a presentation containing a picture of the app and a description of its features. For more consistency, I use the same app design in every domain, i.e., app presentations in one domain have the same color, font, logo, and app structure. Every app within a domain is unique enough to stand alone but fits into an overall concept. Some apps are adaptations of existing apps by adding further features to achieve additional customer value. Other apps are a combination of different app features to create customer value by synergies, while still other apps are new ideas that, as far as I know, do not exist on the app market in this form at the time of creation. In doing so, I consider that new idea generation in practice also consists of different degrees of innovativeness and that new ideas create customer value at various levels (Forés and Camisón 2016; He and Wong 2004; Schmidt, Sarangee, and Montoya 2009).[2] I include some apps in the Appendix.

[2] I ask participants to what extent they perceive the features of the presented app as new. I measure *Newness* on a 7-point Likert-Scale ranging from not at all new (1) to very new (7). The descriptives reveal that the mean value for the various app ideas ranges between 4.23 and 5.43 for the full sample and between 4.62 and 6.03 for the target group sample. Thus, all app ideas have a medium to high degree of novelty. This provides evidence that the app ideas developed for the study are suitable for analyzing indicators of customers' purchase intention for new ideas.

Examples of app adaptions. *Train&Adapt*: This app offers video instructions for various workouts, a feature already offered by several workout apps on the market. However, customers usually can only decide before the workout which intensity and duration they prefer and whether they want to train with or without equipment. In addition, as far as I know, current workout apps only allow customers to rate the entire workout at the end. In contrast, with Train&Adapt, customers can adapt the intensity, duration, and equipment during the workout to automatically adjust the following exercises. In addition, it allows customers to rate each workout exercise individually so that the upcoming exercises are automatically adjusted. *RestaurantFinder*: Restaurant search apps usually offer filters for the type of food, price, and location. I customize these apps so that the app automatically scans restaurants' online menus to show those restaurants that fit customers' diets. To do this, customers can specify their diet in the app, determine whether it is a food intolerance or a diet, and enter a city. In addition, customers can book a table or order food directly in the app.

Examples of feature combinations. *OrgaReunions*: With this app, customers can create a list of tasks they want to organize with friends for an upcoming reunion, assign responsible persons to each task, and track the status of the tasks with checkpoints. Each invited friend can customize the list. In addition, customers can chat directly via the app with one responsible person or with everyone by starting a chat on a specific subject. This helps friends to keep track of important information. Thus, I combine features of planning apps and communication apps. *OnlineSouvenirs:* Customers can buy souvenirs in the in-app online shop. The purchased items are securely packed for the flight and delivered to a pick-up point at the specified airport, where customers return home. The most convenient pick-up location and time are automatically determined based on the flight details, such as departure time and gate. This app offers customers the advantage of not worrying about packing all souvenirs safely during the trip and for the return flight. It combines an online souvenir store with a delivery app.

Examples of new app ideas. *StopoverTime*: This app allows customers to find places to spend time during stopovers. Based on the airport and the flight details, the remaining time for check-in, boarding, and take-off is calculated, and places are recommended that can be visited within the remaining time. For each recommendation, customers receive information about the best travel options to the place, the travel time to the place, and the time available there. *AllInOne*: In this app, customers can add online shops where they have recently ordered items. In-app integration automatically transfers information from the orders to the app. The online stores receive a notification to deliver the orders to the supplier's warehouse, where all orders are collected. All orders are then delivered together at a preferred time slot and location. *Track&Train*: With this app, customers can track how accurately they execute every exercise by video filming themselves during a workout. The app automatically detects correct and incorrect executions and displays green and red lines accordingly. Additionally, customer receive real-time cues to correct and improve their execution.

Indicators of product impressions

I determine the following indicators related to product impressions: Usefulness, Interest, Excitement, Design, Functionality, Quality, Benefits, Convenience, Ease of Use, and Clearness. All these indicators provide information about customers' impressions of functional aspects of new ideas and can, therefore, be clearly distinguished from indicators about customers' problems. In the following, I describe each indicator exemplary for *Track&Train*.

Usefulness. Based on Davis (1989), I define usefulness as an indicator of purchase intentions. Firms need to know the degree of usefulness to select those new ideas that customers require most. The more useful a new idea is perceived, the more likely customers buy it (Claudy, Garcia, and O'Driscoll 2015; Sun and Zhang 2021; Thompson, Hamilton, and Rust 2005).

> *What is your impression of the app in terms of the following criteria? – The app is very useless (1) to the app is very useful (7)*

Interest, Excitement. Besides usefulness, new ideas should also offer emotional value by being interesting and exciting. Emotional value can add arguments that go beyond the functional value of the features (Chitturi, Raghunathan, and Mahajan 2007; Sun and Zhang 2021).

> *What is your impression of the app in terms of the following criteria? – The app is very boring (1) to the app is very interesting (7)*
>
> *What is your impression of the app in terms of the following criteria? – The app is very unexciting (1) to the app is very exciting (7)*

Functionality. Customers are more likely to purchase new ideas that perform well and are capable of doing what they intend to do (Homburg, Schwemmle, and Kuehnl 2015).

> *Using the app would allow me to track how accurately I execute exercises more easily. – Strongly disagree (1) to strongly agree (7)*

Design. Customers' first impression is often based on the design of new ideas. Thus, a good visual appeal is crucial in creating awareness. A new idea that stands out visually is more likely to be noticed by potential buyers, which can increase purchase intention (Goode, Dahl, and Moreau 2013; Homburg, Schwemmle, and Kuehnl 2015).

> *What is your impression of the app in terms of the following criteria? – The app looks very unappealing (1) to the app looks very appealing (7)*

Quality, Benefits, Convenience. I derive these indicators from prior research on perceived value. Customers analyze the absolute quality and benefit offered by a new idea. Additionally, they weigh the value of using the new idea and paying money against not using it and paying zero (Chang and Tseng 2013; Hsu and Lin 2015; Sweeney and Soutar 2001).

> *What is your impression of the app in terms of the following criteria? – The app is of very low quality (1) to the app is of very high quality (7)*
>
> *To what extent can the app add benefits for you? – The app adds no benefits at all (1) to the app adds lots of benefits (7)*
>
> *It would be more convenient to use the app to track how accurately I execute exercises than without the app. – Strongly disagree (1) to strongly agree (7)*

Ease of Use. According to Davis's TAM (1989), ease of use is defined by the extent to which customers can easily use a new idea without much learning effort. Better ease of use should contribute to increased purchase intention (Claudy, Garcia, and O'Driscoll 2015).

> *I would find the app easy to use to track how accurately I execute exercises. – Strongly disagree (1) to strongly agree (7)*

Clearness. Customers should easily understand how to use a new idea before purchasing it. This influences customers' understanding of its value and, consequently, their purchase intention (Claudy, Garcia, and O'Driscoll 2015; Mukherjee and Hoyer 2001).

> *It is clear and understandable how to use the app to track how accurately I execute exercises. – Strongly disagree (1) to strongly agree (7)*

Indicators of customer problems

I determine the following indicators related to customer problems: Purpose, Degree of Problems, Level of Difficulties, Behavioral Fit, Problem Awareness, Complain Level, Solution Search, Priority, Improvement, and Comparative Gain. I derive the indicators of customer problems from the JtbD literature, which determines the dimensions related to this concept (see: Christensen et al. 2016a; 2016b; Ulwick 2005; Ulwick and Bettencourt 2008)[3]. In the following, I describe each indicator exemplary for *Track&Train*.

Purpose. According to the JtbD concept, customers want to fulfill a specific job and buy new ideas that support them in doing so. This means that every new idea should have a clear purpose for customers for which they would buy it. This purpose should support customers in fulfilling their specific jobs by reducing problems. For instance, the purpose of Track&Train is to support customers in executing exercises more accurately, as it might be difficult for customers to track their accuracy without the app. To understand whether customers are willing to buy a new idea,

[3] I derive all indicators in this section "Indicators of customer problems" based on the definitions, dimensions and principles defined in this literature. As the individual indicators do not refer to a single reference, but to the concept defined by Christensen et al. 2016a; 2016b; Ulwick 2005; Ulwick and Bettencourt 2008, I do not repeat the literature references for each indicator in this section.

firms need to find out how frequently customers are confronted with the purpose of the new idea to understand how often a customer would use it.

> *How frequently do you perform workouts where the correct execution is very important? – Never (1) to frequently (7)*

Degree of Problems. In addition to the frequency of a job occurrence, customers must also experience frequent problems when performing the job. By asking customers about the degree of problems, firms can find out how often customers face the problems the new idea addresses. The more frequently customers have problems accomplishing the job, the more likely it is that they have not yet found an adequate solution that helps them accomplish the job, and the more likely they will buy a new idea to solve the problems. Thus, firms should ask how frequently customers experience problems fulfilling their jobs.

> *How frequently do you have problems tracking how accurately you execute an exercise? – Never (1) to frequently (7)*

Level of Difficulties. Firms need to validate whether the features offered by a new idea solve each component of customers' problem. Therefore, firms need to understand the extent to which customers experience difficulties the new idea solves. The more likely customers experience difficulties the new idea solves, the more likely they buy it. Each feature needs to be converted into problem statements to ask customers about the level of difficulties they experience.

> *Feature 1: When doing a workout, to what extent do you find it difficult to know how accurately you execute each exercise? – Very easy (1) to very difficult (7)*

> *Feature 2: When doing a workout, to what extent do you find it difficult to know how to correct your execution of the exercise? – Very easy (1) to very difficult (7)*

Behavioral Fit. Another aspect of purchase intentions is the extent to which customers can easily integrate the new idea into their daily lives. The more the new idea matches the customer's current behavior, the more likely they are to buy it compared to other offerings. A greater behavioral fit makes integrating it into their routines and habits easier.

> *To what extent does the app fit the way you usually track how accurately you execute exercises? – Very poor fit (1) to very good fit (7)*

Problem Awareness, Complain Level. The more customers are aware of a problem, and the more they complain about it, the more willing they are to purchase a solution.

> *I have already noticed that the options I currently have to track how accurately I execute exercises are not ideal. – Strongly disagree (1) to strongly agree (7)*

> *I often complain about the difficulty of tracking how accurately I execute exercises. – Strongly disagree (1) to strongly agree (7)*

Solution Search. Another driver of customers' motivation to find a solution can be whether they already searched for a solution that supports them in reducing problems. Customers who are already and still searching for a solution show a strong desire for a solution. The effort they have already invested can increase their purchase intention if they find the right solution.

> *I have already searched for apps that help me track how accurately I execute exercises. – Strongly disagree (1) to strongly agree (7)*

Priority. Besides customers' awareness that they experience problems, the problem and solution also need to be of high priority for customers. The higher the priority, the more willing they are to take care of the problem and find a solution, and the more likely they are to buy.

> *It is very important for me to execute every exercise accurately. – Strongly disagree (1) to strongly agree (7)*

Improvement, Comparative Gain. The principle behind the JtbD concept is that firms should focus on helping customers to solve problems. Thus, firms should understand how well the new idea solves customers' problems. Therefore, firms should ask customers to what extent they would experience improvements when using it (*improvement*) and how likely they would experience a gain compared to not using it (*comparative gain*). While the improvement measure gives insights on whether the new idea generally adds value by solving their problems and improving their situation, the comparative measure provides further insights on whether the gain of the new idea is big enough to buy it compared to not buying it.

> *The app would enhance my workout experience, as I could execute exercises more accurately. – Strongly disagree (1) to strongly agree (7)*

> *How likely is it that you would execute the exercises more accurately when using the app compared to not using it? – Very unlikely (1) to very likely (7)*

Model variables

The dependent variable of interest is customers' purchase intention. According to previous studies, customers' evaluation based on different indicators leads to an overall impression of the new idea, which in turn influences their purchase intention (Arts, Frambach, and Bijmolt 2011; Breidert, Hahsler, and Reutterer 2006; Homburg, Koschate, and Hoyer 2005). According to this, I define the *Indicators* as independent variables, *Desirability* as the mediator variable representing the overall impression, and *Purchase Intention* as the dependent variable.

I measure *Desirability* on a 7-point Likert Scale, asking participants how desirable an app is, ranging from very undesirable (1) to very desirable (7). I operationalize *Purchase Intention* by customers' willingness to pay (WTP). To measure *Purchase Intention* participants first indicate how likely they would pay a monthly subscription fee for an app regardless of a specific price, from 0% to 100%. Those who indicate a likelihood greater than 0% then indicate the maximum subscription fee they are willing to pay in dollars per month for an app, ranging from $0.10 to $15.00. The final dependent variable *Purchase Intention* ranges from $0.00 to $15.00 based on the indicated WTP and by setting the data to $0.00 in case participants indicated a purchase likelihood of 0%.

Target group sample

In addition to the factors that affect customers' purchase intentions, previous research has analyzed factors that influence the accuracy with which customers can predict their purchase intentions. I consider these factors to determine a subsample that represents a realistic target group. This allows me to test the effects on purchase intention in a more homogenous sample to reduce noise in the model.

According to prior research, customer involvement and innovation behavior impact the accuracy of customers' predictions on their purchase behavior (Arts, Frambach, and Bijmolt 2011; Cui and Wu 2016; Goldsmith and Hofacker 1991; Ozer 2011; Steenkamp and

Baumgartner 1994). Some prior research determines involvement by the personal importance customers attach to a product class. The more important the product class is for customers, the more effort they put into evaluating new ideas of the respective class, and the less noisy the relation between attitude and intention (Arts, Frambach, and Bijmolt 2011; Bart, Stephen, and Sarvary 2014; Candi et al. 2017; Mittal 1995). Other research defines customer involvement as the frequency of customer engagement. The more frequently customers engage in the respective domain, the more knowledgeable they are about the available products and their needs, which increases the accuracy in predicting their purchase intention (Cui and Wu 2016; Ozer 2011; Thompson and Sinha 2008). Besides this, other studies identify innovation behavior as an influence factor. The more customers favor the new over the old and enjoy trying new things, the more likely they are to buy new ideas earlier, as they adopt them sooner. Their attitude formation and purchase intention are more closely linked in time, i.e., their attitude can be more reflective of purchase intention, leading to more accurate predictions (Arts, Frambach, and Bijmolt 2011; Goldsmith and Hofacker 1991; Steenkamp and Baumgartner 1994).

Based on the prior research, the target group sample in this study consists of participants who are highly involved in the respective domain, very open to innovation, and generally willing to pay for an app. Prior research determines involvement by personal importance to a product class (Arts, Frambach, and Bijmolt 2011; Candi et al. 2017; Mittal 1995) and by involvement frequency (Cui and Wu 2016; Thompson and Sinha 2008). I measure *Personal Importance* based on Mittal's product class involvement construct (1995). This construct is measured based on three items: Importance, Interest, and Matter ($\alpha = 0.97$). I measure *Involvement Frequency* based on two items: Past Involvement and Future Involvement ($\alpha = 0.93$). Based on Goldsmith and Hofacker (1991) and Steenkamp and Baumgartner (1994), I measure *Innovation Behavior* based on three items: Openness for New, Openness for Experience, and Openness for Change ($\alpha = 0.95$). In addition, I also consider whether participants in general are willing to pay for an app. The reason is that free apps are often offered on the market, which can influence customers' general payment behavior for apps (Furner and Zinko 2018). I present the factors and items in the Appendix.

Procedures and participants

I recruit participants on the web-based crowdsourcing platform MTurk. To ensure high-quality participation, the pool was restricted to participants with an approval rate of 98% or higher and a minimum of 500 approvals on MTurk (Ahler, Roush, and Sood 2019; Bentley 2021). Participants completing one survey receive a fixed pay of $1.30. On average, participants completed a survey in 16 minutes, resulting in an hourly rate of $4.90.

I uploaded one survey for each of the five domains, resulting in a total of five surveys for this study. Each survey consists of five apps from the same domain. For example, if participants participate in the survey on workout apps, they receive five workout apps and rate them either on product impressions indicators or customer problems indicators. The order of the five apps is randomized to control for order effects when evaluating the apps. Participants can choose the survey domain. Allowing participants to self-select into the domains increases the likelihood that they relate to the target group. However, to increase controllability, they are randomly assigned once to either the product impressions indicators or customer problems indicators. Throughout one survey, the participants rate all five apps on the same type of indicator.

For the survey, participants first indicate whether they are completing the study on a mobile device or computer screen to ensure the app presentations are displayed correctly. After reading the instructions and passing two attention questions, the participants receive the first app presentation and have to familiarize themselves with the app idea. On the next page, the participants answer a comprehension question about the app's objective. They then provide feedback by evaluating the app either on the product impression indicators or the customer problem indicators. After evaluating it, participants indicate their desirability and WTP for the app and proceed to the next app. After evaluating all apps, participants provide information on the target group variables and demographics.

For the final sample, I exclude participants for the following reasons: (1) incompatibility of selected study style (mobile or computer) and used device to ensure that all relevant information was displayed appropriately, as this can influence participants' evaluations of the new ideas, (2) inconsistent information on purchase intention[4] to avoid inattention (3) failed comprehension questions about the app to ensure that answers are not influenced by misunderstanding. The final sample consists of 1'673 participants. 51.64% of participants provided feedback on product impressions, and 48.36% on customer problems.

For the target group sample, I additionally exclude 43 participants due to inconsistencies regarding their involvement level. They indicate a high level of involvement, i.e., in terms of *Personal Importance* and *Involvement Frequency*, but state that they spend 0% of their income on the respective domain. The target group sample consists of 224 participants. 52.23% of participants provided feedback on product impressions, and 47.77% on customer problems.

On average, participants of the full and target sample are 40 years old. 51.94% (46.88%) of the full (target group) sample are female, 45.31% (49.55%) are male, 1.08% (1.79%) are diverse, and 1.67% (1.79%) prefer not to state their gender. The majority of the full (target group) sample has an average annual income of $40,000 to $45,000 ($50,000 to $55,000). On average, participants of the full (target group) sample spend 11% (17%) of their annual income on travel, 7% (11%) on meeting friends, 16% (21%) on nutrition, 4% (7%) on workouts, and 8% (11%) on delivery.

[4] After asking participants on their WTP, I also asked how likely they are willing to use a prototype version of the app for a monthly subscription fee less than or equal to 50% and 25% of their indicated WTP. I excluded participants who are inconsistent by showing a lower likelihood of purchase although the subscription fee decreases.

IV. Results

Models on product impressions

I report the correlations of the product impression indicators in Table 1. Even though some indicators show correlations above 0.8, a further analysis of the variance inflation factor (VIF) shows an overall value of 4.83 for the full sample and 4.75 for the target group sample. A VIF value below 5 indicates a low multicollinearity. Thus, the models need no further adaptation as the variables are not highly collinear in the whole model (O'Brien 2007).

I report the results of the SEMs analyzing the effects of *product impressions* indicators on *Desirability* and, consequently, on *Purchase Intention* in Table 2 (Model 1: full sample | Model 2: target group sample). The fit indices of both models show a good model fit (see: Hu and Bentler 1999; Schermelleh-Engel, Moosbrugger, and Müller 2003). In addition, the model fit improves by narrowing the full sample to the target group sample, as the values of AIC (153'835.801 vs. 19'413.742) and BIC (153'931.370 vs. 19'479.187) decrease from Model 1 to Model 2 (Lin, Huang, and Weng 2017; Schermelleh-Engel, Moosbrugger, and Müller 2003).

In Model 1, the following indicators show significant positive effects on *Desirability,* which significantly influence *Purchase Intention* ($\beta = 0.60$, $p < 0.001$): Usefulness ($\beta = 0.04$, $p = 0.06$), Interest ($\beta = 0.09$, $p < 0.001$), Excitement ($\beta = 0.14$, $p < 0.001$), Design ($\beta = 0.13$, $p < 0.001$), Benefits ($\beta = 0.53$, $p < 0.001$), Convenience ($\beta = 0.21$, $p < 0.001$). Benefits shows the highest coefficient across all indicators, i.e., it has the strongest influence in the model.

The following indicators also show in Model 2 significant positive effects on *Desirability,* which in turn significantly influence *Purchase Intention* ($\beta = 0.78$, $p < 0.001$): Usefulness ($\beta = 0.14$, $p = 0.02$), Interest ($\beta = 0.20$, $p < 0.001$), Design ($\beta = 0.24$, $p < 0.001$), Benefits ($\beta = 0.30$, $p < 0.001$), Convenience ($\beta = 0.16$, $p = 0.002$). Compared to Model 1, Ease of Use shows a significant positive ($\beta = 0.13$, $p = 0.02$), and Clearness a significant negative ($\beta = -0.15$, $p = 0.008$) effect. The following indicators show an insignificant effect in Model 2 compared to Model 1: Excitement ($\beta = 0.04$, $p = 0.347$), Functionality ($\beta = 0.09$, $p = 0.113$), and Quality ($\beta = -0.04$, $p = 0.348$). Thus, while Ease of Use only matters to the target group, Excitement, Functionality and Quality do not significantly impact their purchase intention compared to the full sample.[5] The indicator Benefits has the strongest influence also in Model 2.[6]

The path coefficient of *Desirability* on *Purchase Intention* increases from Model 1 to Model 2 (0.60 vs. 0.78), indicating that this effect becomes stronger when narrowing the sample to the target group. In addition to the lower values of the indices AIC and BIC of Model 2 compared to Model 1, this provides further evidence to focus on the target group instead of the full sample. As stated in prior literature, the factors used to determine the target group increases the accuracy with which customers can state their purchase intention based on their evaluations (Arts, Frambach, and Bijmolt 2011; Cui and Wu 2016; Goldsmith and Hofacker 1991; Steenkamp and Baumgartner 1994; Ozer 2011). In line with this, the target group increases the accuracy in predicting customers' purchase intention by reducing noise in the model.

As the accuracy in predicting purchase intentions improves for the target group sample, firms should consider the defined factors when selecting participants for customer feedback studies. Asking only those participants who are highly involved, highly open to innovation, and, in general, willing to pay can increase the accuracy in identifying the most promising new ideas. The results of the target group model show that Usefulness and Ease of Use significantly influence customers' purchase intention in line with Davis' TAM (1989). The fact that the indicator Benefits has the strongest influence on purchase intentions also aligns with prior literature.

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[5] As the VIF is below 5, it can be expected that the negative effect of Clearness is not caused by multicollinearity issues (O'Brien 2007). To provide further evidence that multicollinearity issues should not matter, I analyze the target group model by combining variables into latent constructs based on a factor analysis. In the case of multicollinearity issues, the model fit should improve, however, the fit of the model with latent constructs decreases (RMSEA = 0.09; AIC = 19'723.491; BIC = 19'902.375; CFI = 0.97; TLI = 0.96; SRMR = 0.03). Even though prior research indicates that it is important to clearly understand how to use a new idea (Claudy, Garcia, and O'Driscoll 2015; Mukherjee and Hoyer 2001), another line of research argues that high clearness can lead to simplification impressions, i.e., a new idea is perceived as overly simplistic which reduces customers desirability (Pocheptsova, Labroo, and Dhar 2010). Thus, an explanation of the negative effect of Clearness can be that customers perceive new ideas that are too clearly understandable as too simple ideas in terms of their usage which reduces purchase intentions. This aligns with research on the paradox of simplicity, i.e., customers want user-friendly but not too simplistic perceived products in terms of their usage (Eytam, Tractinsky, and Lowengart 2017).

[6] The statistical inferences remain the same in terms of indirect effects of the indicators on *Purchase Intention*, indicating that the path is mediated by *Desirability*.

According to prior literature on product impressions, firms need to focus on understanding whether customers can derive the greatest benefit from a new idea and its features (Adams, Day, and Dougherty 1998; Sweeney and Soutar 2001; Thompson, Hamilton, and Rust 2005). The results also reveal that firms should focus on interesting and appealing new ideas to increase purchase intention (Interest and Design). Thereby, the new idea should be sufficiently convenient for customers to use it in comparison to not use it (Convenience).

TABLE 1
Product Impressions – Correlation Tables

Panel A: Full sample

	1	2	3	4	5	6	7	8	9	10
1 Usefulness	1.00									
2 Interest	0.85	1.00								
3 Excitement	0.81	0.86	1.00							
4 Design	0.81	0.83	0.85	1.00						
5 Functionality	0.73	0.71	0.67	0.70	1.00					
6 Quality	0.74	0.76	0.76	0.81	0.65	1.00				
7 Benefits	0.86	0.81	0.80	0.79	0.71	0.70	1.00			
8 Convenience	0.75	0.72	0.71	0.72	0.84	0.65	0.76	1.00		
9 Ease of Use	0.60	0.56	0.53	0.57	0.72	0.59	0.57	0.64	1.00	
10 Clearness	0.56	0.53	0.49	0.55	0.69	0.59	0.52	0.58	0.86	1.00

Panel B: Target group sample

	1	2	3	4	5	6	7	8	9	10
1 Usefulness	1.00									
2 Interest	0.83	1.00								
3 Excitement	0.78	0.81	1.00							
4 Design	0.79	0.80	0.82	1.00						
5 Functionality	0.71	0.68	0.65	0.67	1.00					
6 Quality	0.73	0.70	0.74	0.77	0.62	1.00				
7 Benefits	0.82	0.74	0.76	0.75	0.67	0.67	1.00			
8 Convenience	0.74	0.70	0.69	0.73	0.84	0.65	0.72	1.00		
9 Ease of Use	0.62	0.56	0.57	0.61	0.72	0.58	0.59	0.69	1.00	
10 Clearness	0.56	0.52	0.53	0.59	0.68	0.59	0.53	0.63	0.85	1.00

Table 1 presents the correlations of the product impressions indicators. Panel A shows the correlation results of the full sample and Panel B of the target group sample. All correlations are significant at $p \leq 0.01$.

TABLE 2
Product Impressions – SEM

Desirability	*Model1*	*Model2*
Usefulness	0.04 (0.02) p=0.06*	0.14 (0.06) p=0.02**
Interest	0.09 (0.02) p<0.001***	0.20 (0.05) p<0.001***
Excitement	0.14 (0.02) p<0.001***	0.04 (0.04) p=0.347
Design	0.13 (0.02) p<0.001***	0.24 (0.05) p<0.001***
Functionality	-0.05 (0.02) p=0.004***	0.09 (0.06) p=0.113
Quality	-0.05 (0.02) p=0.002***	-0.04 (0.04) p=0.348
Benefits	0.53 (0.02) p<0.001***	0.30 (0.04) p<0.001***
Convenience	0.21 (0.02) p<0.001***	0.16 (0.05) p=0.002***
Ease of Use	-0.02 (0.02) p=0.395	0.13 (0.06) p=0.02**
Clearness	0.01 (0.02) p=0.681	-0.15 (0.06) p=0.008***
Constant	-0.44 (0.05) p<0.001***	-0.81 (0.18) p<0.001***

Purchase Intention		
Desirability	0.60 (0.02) p<0.001***	0.78 (0.06) p<0.001***
RMSEA	0.05	0.05
AIC	153’835.801	19’413.742
BIC	153’931.370	19’479.187
CFI	0.99	0.99
TLI	0.97	0.97
SRMR	0.01	0.02
R^2	80.80%	78.71%
N	4’321	580

Table 2 presents the SEM consisting of the ten product impressions indicators as independent variables, *Desirability* as mediator, and *Purchase Intention* as dependent variable. Model 1 includes the full sample. Model 2 includes participants who are highly involved, highly open to innovations, and generally willing to pay for an app (target group sample). * p ≤ 0.10; ** p ≤ 0.05; *** p ≤ 0.01; p-levels are two-tailed.

Models on customer problems

I report the correlation analysis of the customer problems indicators in Table 3. The results of the correlation analysis show that most indicators have a correlation below 0.8 in the full sample and the target group sample. A further analysis of the variance inflation factor (VIF) shows an overall value of 2.72 for the full sample and 3.35 for the target group sample. As a VIF value below 5 indicates a low multicollinearity, the models need no further adaptation as the variables are not highly collinear in the whole model (O’Brien 2007).

I report the results of the SEMs analyzing the effects of customer problem indicators on *Desirability* and, consequently, on *Purchase Intention* in Table 4 (Model 1: full sample | Model 2: target group sample). As the fit indices CFI, TLI, and SRMR are within the cutoff values for a good model fit and RMSEA is below an acceptable level of 0.08, the two models show an overall good fit (see: Hu and Bentler 1999; Schermelleh-Engel, Moosbrugger, and Müller 2003). In addition, the model fit improves by narrowing the full sample to the target group sample as the values decrease from Model 1 to Model 2 regarding the indices AIC (170’345.059 vs. 21’872.132) and BIC (170’439.675 vs. 21’936.168) (Lin, Huang, and Weng 2017; Schermelleh-Engel, Moosbrugger, and Müller 2003).

In Model 1, the following indicators show significant positive effects on *Desirability,* which in turn significantly influence *Purchase Intention* ($\beta = 0.55$, $p < 0.001$): Purpose ($\beta = 0.04$, $p = 0.001$), Degree of Problem ($\beta = 0.09$, $p < 0.001$), Behavioral Fit ($\beta = 0.21$, $p < 0.001$), Problem Awareness ($\beta = 0.03$, $p = 0.05$), Solution Search ($\beta = 0.02$, $p = 0.04$), Priority ($\beta = 0.09$, $p<0.001$), Improvement ($\beta = 0.22$, $p < 0.001$), and Comparative Gain ($\beta = 0.35$, $p < 0.001$). Comparative Gain shows the strongest influence on *Desirability*.

The following indicators also show in Model 2 significant positive effects on *Desirability,* which in turn significantly influence *Purchase Intention* ($\beta = 0.71$, $p < 0.001$): Degree of Problem ($\beta = 0.06$, $p = 0.08$), Behavioral Fit ($\beta = 0.28$, $p < 0.001$), Priority ($\beta = 0.11$, $p = 0.003$), Improvement ($\beta = 0.16$, $p < 0.001$), and Comparative Gain ($\beta = 0.40$, $p < 0.001$). Comparative Gain has the strongest influence on *Desirability* also in Model 2 and shows an even higher coefficient. Thus, this indicator impacts the purchase intention of the target group even more compared to the full sample. Compared to Model 1, the following indicators show insignificant effects: Purpose ($\beta = 0.03$, $p = 0.326$), Problem Awareness ($\beta = -0.01$, $p = 0.866$), and Solution Search ($\beta = 0.00$, $p = 0.956$). Thus, these indicators have no significant impact on the purchase intention of the target group compared to the full sample.[7]

The coefficient of the path effect from *Desirability* on *Purchase Intention* increases from Model 1 to Model 2. This indicates that the effect also becomes stronger for the target group sample of the customer problems model. As the values of the indices AIC and BIC also

[7] The statistical inferences remain the same in terms of indirect effects of the indicators on *Purchase Intention*, indicating that the path is mediated by *Desirability*.

decrease from Model 1 to Model 2, it provides evidence that firms should focus on the target group sample when considering information on customer problems. The target group increases the accuracy in predicting customers' purchase intention by reducing noise in the model.

The principle behind the JtbD concept is that firms should focus on solutions that effectively address customers' problems. In line with the results of the target group sample, this means that firms should focus on how well a new idea improves the customers' situation by solving their problems effectively (Improvement). More importantly, firms should understand the comparative gain customers receive from their new idea compared to not using it to increase their purchase intentions (Comparative Gain). In addition, based on the JtbD concept it is crucial to understand to what extent and how often customers experience a certain problem the new idea can solve. The results reveal that the frequency of experiencing problems significantly increases customers' purchase intention (Degree of Problem), whereas the level of difficulties does not. Thus, it is more important that a problem occurs frequently in customers' live for an increased purchase intention, regardless of how difficult customers perceive it to be. Additionally, for a higher purchase intention, it is crucial that the solution to the problem should be of high priority for customers (Priority) and that the new idea should fit current customer behavior to be easily integrated into their daily lives (Behavioral Fit).[8]

[8] The aim is to analyze which indicators firms should focus on when acquiring information on product impressions and/or customer problems. Thus, the focus of this study is the empirical analysis of purchase intention drivers for each type of information by identifying the dimensions related to each type. For clearer tests and higher controllability, participants were randomized to evaluate the new ideas either based on product impressions or customer problems indicators. However, this does not allow for detailed direct statistical comparisons, for instance, for testing whether the R^2 of both types of information are statistically different from each other due to the data structure of the indicators, i.e., no nested or within design. Nevertheless, comparing the absolute R^2 values of the target group model between the product impressions model (78.71%) and the customer problems model (81.07%) shows high and similar values. It can be assumed that the indicators predict the variance in purchase intention similar well within each model. In addition, the target group models also show rather an equal number of indicators (product impressions: 6 | customer problems: 5) that significantly predict customers' purchase intention.

TABLE 3
Customer Problems – Correlation Tables

Panel A: Full sample

	1	2	3	4	5	6	7	8	9	10
1 Purpose	1.00									
2 Degree of Problems	0.58	1.00								
3 Level of Difficulties	0.36	0.69	1.00							
4 Behavioral Fit	0.50	0.59	0.52	1.00						
5 Problem Awareness	0.41	0.68	0.69	0.57	1.00					
6 Complain Level	0.45	0.69	0.65	0.58	0.76	1.00				
7 Solution Search	0.40	0.47	0.38	0.47	0.46	0.57	1.00			
8 Priority	0.51	0.58	0.48	0.61	0.55	0.57	0.40	1.00		
9 Improvement	0.48	0.63	0.59	0.70	0.68	0.64	0.44	0.72	1.00	
10 Comparative Gain	0.46	0.62	0.60	0.71	0.66	0.62	0.40	0.67	0.82	1.00

Panel B: Target group sample

	1	2	3	4	5	6	7	8	9	10
1 Purpose	1.00									
2 Degree of Problems	0.58	1.00								
3 Level of Difficulties	0.45	0.73	1.00							
4 Behavioral Fit	0.53	0.63	0.58	1.00						
5 Problem Awareness	0.48	0.65	0.66	0.60	1.00					
6 Complain Level	0.47	0.68	0.65	0.60	0.79	1.00				
7 Solution Search	0.42	0.43	0.36	0.48	0.47	0.54	1.00			
8 Priority	0.52	0.56	0.52	0.69	0.55	0.61	0.46	1.00		
9 Improvement	0.46	0.56	0.56	0.72	0.66	0.63	0.41	0.75	1.00	
10 Comparative Gain	0.49	0.54	0.58	0.73	0.64	0.62	0.41	0.72	0.80	1.00

Table 3 presents the correlations of the customer problems indicators. Panel A shows the correlation results of the full sample and Panel B of the target group sample. All correlations are significant at $p \leq 0.01$.

TABLE 4
Customer Problems

Desirability	*Model1*	*Model2*
Purpose+	0.04 (0.01) p=0.001***	0.03 (0.03) p=0.326
Degree of Problems+	0.09 (0.01) p<0.001***	0.06 (0.03) p=0.08*
Level of Difficulties+	0.00 (0.01) p=0.912	0.00 (0.03) p=0.888
Behavioral Fit	0.21 (0.01) p<0.001***	0.28 (0.04) p<0.001***
Problem Awareness	0.03 (0.01) p=0.05*	-0.01 (0.03) p=0.866
Complain Level	0.02 (0.01) p=0.186	0.02 (0.03) p=0.512
Solution Search	0.02 (0.01) p=0.04**	0.00 (0.02) p=0.956
Priority	0.09 (0.01) p<0.001***	0.11 (0.04) p=0.003***
Improvement	0.22 (0.02) p<0.001***	0.16 (0.04) p<0.001***
Comparative Gain	0.35 (0.02) p<0.001***	0.40 (0.04) p<0.001***
Constant	-0.18 (0.05) p<0.001***	-0.17 (0.13) p=0.204

+ Due to multiple features, some apps tackle two purposes and respectively two problems leading to two questions per indicator. In addition, every feature should be translated into a difficulty statement, leading to two to three questions. For the analysis, I combine the questions per indicator in one construct, as all questions are equally important in describing the indicator.

Purchase Intention		
Desirability	0.55 (0.02) p<0.001***	0.71 (0.05) p<0.001***
RMSEA	0.07	0.07
AIC	170’345.059	21’872.132
BIC	170’439.675	21’936.168
CFI	0.97	0.98
TLI	0.94	0.95
SRMR	0.03	0.02
R^2	75.20%	81.07%
N	4’055	528

Table 4 presents the SEM consisting of the ten customer problems indicators as independent variables, *Desirability* as mediator, and *Purchase Intention* as dependent variable. Model 1 includes the full sample. Model 2 includes participants who are highly involved, highly open to innovations, and generally willing to pay for an app (target group sample). * p ≤ 0.10; ** p ≤ 0.05; *** p ≤ 0.01; p-levels are two-tailed.

V. Conclusion

In this study, I investigate the drivers of customers’ purchase intention. Therefore, I develop app presentations and quantitative indicators of product impressions and customer problems. The product impression indicators refer to customers’ opinions regarding the functional aspects of new ideas. The indicators for customer problems are derived from the JtbD literature, which focuses on customer problems and the degree to which a new idea solves them. I run structural equation models to test the drivers of customers’ purchase intention. Apart from the full sample, I run a further model considering a subsample likely to represent a realistic target group. The target group consists of highly involved participants, who are also highly open to innovations and generally willing to pay for an app.

The results show an improved model fit by narrowing the sample to the target group for both types of information. As the model fit improves for the target group sample, firms should consider these factors when selecting participants for customer feedback studies. The target group models reveal that six product impression indicators (Usefulness, Interest, Design, Benefits, Convenience, Ease of Use) and five customer problems indicators (Degree of Problems, Behavioral Fit, Priority, Improvement, Comparative Gain) have a significant positive influence on *Desirability*, which influence significantly *Purchase Intention*.

I contribute to research and practice by empirically investigating how product impressions and customer problems indicators influence customers' purchase intentions. Additionally, I contribute by translating the qualitatively defined JtbD concept into quantitative indicators. For research, it allows the design of experiments in which participants can be provided with information on product impressions and customer problems, as the same measurement level increases controllability regarding the provided information. In practice, the quantitative nature can support decision-making by increasing the comparability across new ideas.

I randomize participants to evaluate the new ideas either on product impressions or customer problems indicators. This increases the controllability, for instance, by canceling out individual differences of participants. This is particularly important to clearly test each type of information individually and to collect market information for future decision-making experiments. However, it does not allow for more detailed direct comparisons of the two types of information. Further research can provide more insights by directly comparing them.

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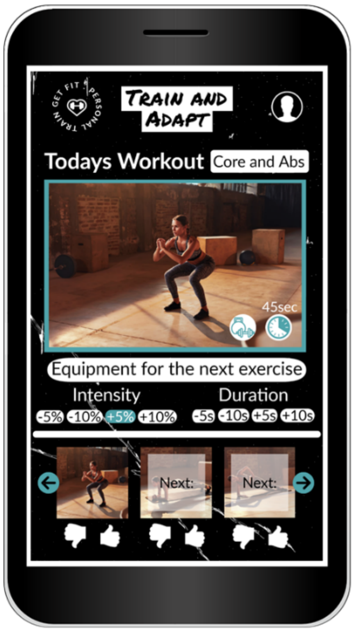
Appendix

Examples of app presentations

-- Train&Adapt --



Adjust the exercises during the workouts

Follow the video instructions for your workout. During the 15-second break between exercises, you can decide whether you want to continue with or without equipment and whether you prefer a different intensity or exercise duration so that the next exercises will be adjusted. If you don't want to adjust anything, just take a 15-second rest and follow the upcoming workout instructions.

Rate the exercises during or after the workout. The exercises in the current workout and of upcoming workouts will be adjusted according to your likes and dislikes.

-- RestaurantFinder --

Find restaurants offering meals that fit your diet

Select which foods you would like to eat and those you do not eat, and define whether this is for diet reasons or due to food intolerance.

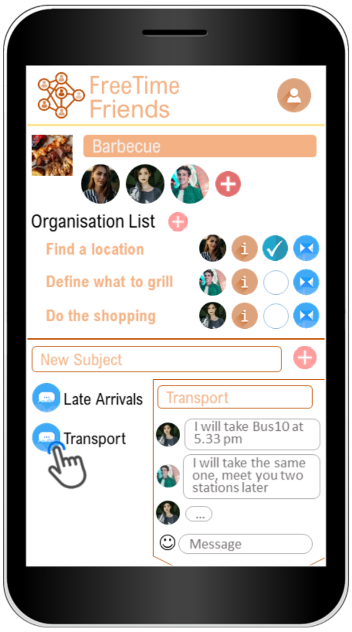
Select the city where you want to find a restaurant and which type of meal you prefer.

The app automatically scans the menus of all restaurant websites in your selected city and displays those restaurants offering meals that fit your diet.

Get an easy overview of the restaurant menus and save your favorites.

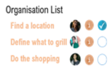
Book a table directly in the app or order your food by delivery.

-- *OrgaReunions* --

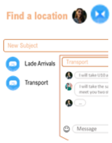


Organize everything for a reunion with your friends

Add a reunion profile.



Create a list of things to organize with your friends. Everyone invited can add tasks and mark themselves as the responsible person. With the checkpoints, everyone keeps track of what is already organized and what is not.



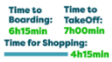
If you need to communicate with your friends, you can either chat directly with a responsible person by clicking the chat icon next to the task, or you can start chats with everyone by setting up a chat for a specific subject.

As everything about one topic is communicated in one chat, you can easily keep track of what has already been communicated and agreed upon without endless searching.

-- *OnlineSouvenirs* --

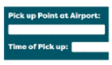
Buy souvenirs online and pick them up at the airport

Name the airport you are returning home from and your flight number for details.



Based on your flight details, your remaining time for souvenir shopping is calculated.

Use the online shop in the app to choose from a wide selection of typical souvenirs and to complete your order. You can use the online shop already while traveling or during your time at the airport as long as you complete your order within the remaining time for shopping (displayed above the online shop).



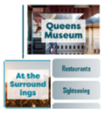
The items purchased online will be perfectly packed for the flight and delivered to a pick-up location at the airport. The most convenient pick-up location and time will be automatically determined based on your gate and flight time. Check the map to find the pick-up point easily.

-- StopoverTime --

Find places to spend your time there during a stopover

Name the airport you are currently at and your flight number for details.

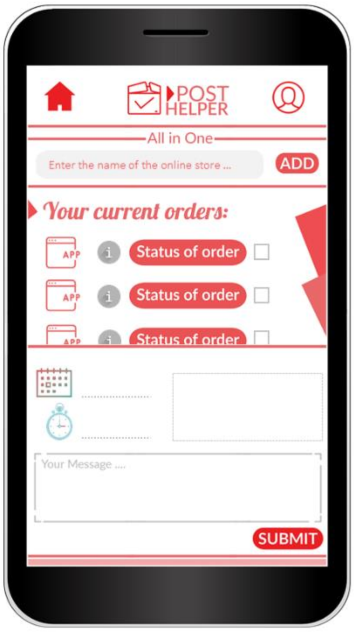
Your remaining time until check-in, boarding, and take-off is calculated and displayed.



Based on your remaining time, places are recommended for where you can spend your free time during a stopover. Depending on the length of the stopover you can choose between places at the airport, the surrounding area or the nearest city. In addition, decide what you would like to do during a stopover (e.g. shopping, sightseeing).

For each recommendation, you receive information about the travel time to the place and the time available there. In addition, the best mode of transport is recommended with all options shown.

-- AllInOne --

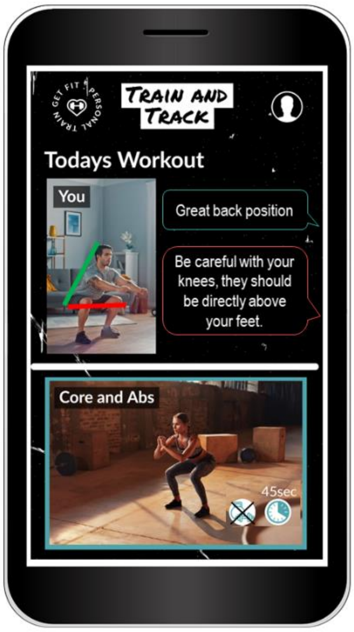


Bundle all your orders into one delivery

Add every online store where you have recently ordered items.

Through in-app integration, information from your orders will be automatically transferred into the app.

The online stores will receive a notification to deliver the orders to our warehouse, where all your orders will first be collected and then delivered all together to you at your preferred time slot and address.



Track the accuracy of your exercise execution

Follow the video instructions of a workout.

Track how accurately you execute every exercise by video filming yourself. The app will automatically detect correct and incorrect executions and display green and red lines accordingly. Additionally, you will receive real-time cues so that you can correct and improve your execution.

Target Group		
Items	**Question** **(exemplary for workout survey)**	**Reference**
Personal Importance		Arts, Frambach, and Bijmolt 2011; Candi et al. 2017; Mittal 1995
Importance	Doing workouts is very important to me. – Strongly disagree (1) to Strongly agree (7)	
Interest	I have a strong interest in doing workouts. – Strongly disagree (1) to Strongly agree (7)	
Matter	For me, doing workouts matters a lot. – Strongly disagree (1) to Strongly agree (7)	
Involvement Frequency		Cui and Wu 2016; Thompson and Sinha 2008
FQ Past	How frequently did you do workouts in the last 12 months? – Never (1) to Frequently (7)	
FQ Future	How frequently do you plan to do workouts in the next 12 months? Please make a rough estimate. – Never (1) to Frequently (7)	
Innovation Behavior		Goldsmith and Hofacker 1991; Steenkamp and Baumgartner 1994
Openness for New	I like to try new and different things rather than to continue doing and using the same old things. – Strongly disagree (1) to Strongly agree (7)	
Openness for Experiences	I am continually seeking new ideas and experiences. – Strongly disagree (1) to Strongly agree (7)	
Openness for Change	I like to experience novelty and change. – Strongly disagree (1) to Strongly agree (7)	
General Willingness to Pay	I am generally willing to pay a monthly subscription for new workout apps if it offers me sufficient benefits. – Strongly disagree (1) to Strongly agree (7)	Furner and Zinko 2018

ESSAY 2

The Interactive Dynamics of Information Separation and Information Order

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Abstract

Effective idea selection is crucial for long-term success but poses major challenges for firms. Faced with limited resources, firms are confronted with the challenge of selecting ideas with the greatest potential to ensure effective allocation of resources. To support idea selection, top management requires information from different departments, creating the challenge for firms how to provide all decision-relevant information to top management. As different departments generate information with a time gap, it raises the question of whether firms should provide information to top management as soon it is made available for reporting (high information separation) or combine all information in one report (low separation) before providing it to top management. I analyze the effect of information separation on decision performance contingent on the innovation approach adopted by firms, either market-first or product-first, which influences the order in which product and market information is disseminated to top management. Drawing on cognitive psychology theory, I predict that under market-first decision performance increases with low compared to high separation. I also predict that this positive effect is weaker under product-first compared to market-first. To test my hypotheses, I run an online experiment using Prolific. My experiment using real market information supports my predictions. This study emphasizes an interactive dynamic of information separation and information order.

Keywords: information provision, information separation, information order, idea selection, decision performance, innovation approach

I. Introduction

Idea selection is a crucial but highly challenging task in new product development (Cooper 2013; Hammedi, van Riel, and Sasovova 2011; Markham 2013; Sukhov et al. 2021). Facing limited resources, the main challenge is to identify and select those ideas with the highest potential to allocate resources to the most promising ones (Berg 2016; Dziallas 2020). Consequently, careful idea evaluation is crucial for idea selection to avoid misjudging the potential of new ideas (Kruft et al. 2019; Martinsuo and Poskela 2011; Schmidt, Sarangee, and Montoya 2009). For careful idea evaluation and selection, top management requires various types of information from the departments involved in the innovation process. Since multiple departments, such as R&D and marketing, are involved in the innovation process and generate different decision-relevant information, firms need to ensure accessibility and provision of relevant information to top management to facilitate idea selection (Adams, Day, and Dougherty 1998; Cui and Xiao 2019; Kruft et al. 2019).

For innovation, firms adopt either a more product-oriented approach (hereafter: product-first), in which product information determines the primary steps, or a more market-oriented approach (hereafter: market-first), in which market information forms the starting point for innovation (Gatignon and Xuereb 1997; Homburg and Pflesser 2000; Kohli and Jaworski 1990; Parry and Song 2010). The different starting points influence the order in which information is predominantly disseminated to top management. Under product-first, firms disseminate product information as soon as possible to update top management on new ideas, their features, and benefits. In contrast, under market-first, firms disseminate market information earlier on to keep top management updated on market insights and customer opinions (Cui and Xiao 2019; MacCormack and Verganti 2003).

Although the approach differs, prior research provides evidence that both types of information – product and market – are essential for effective idea selection and should be provided to top management at some time (Martinsuo and Poskela 2011; Parry and Song 2010;

Payne, Frow, and Eggert 2017; Tzokas, Hultink, and Hart 2004). However, in dependance on the approach, the departments such as R&D and marketing generate and prepare information for reporting at different stages, i.e., with a time gap, resulting in an information separation (Dougherty 1992a; Hart et al. 2003; Tzokas, Hultink, and Hart 2004). This raises the question of whether information should be provided when available, i.e., with high separation, or whether it is more effective to wait until all information is available to combine them for top management, i.e., low separation. To support idea selection, it is crucial for firms with different innovation approaches to understand how the time gap between providing various types of information affects decision performance. Thus, I investigate the effect of information separation on decision performance by considering how this effect is moderated by information order.

Investigating this RQ is important because providing information as soon as it is available for reporting, i.e., with high separation, could be beneficial to ensure that top management is always informed and up to date. However, research in information processing indicates that high separation might be less beneficial for decision performance in settings where various pieces of information need to be processed (Hilbig et al. 2015; Wickens and Carswell 1995). Previous research shows that differences in impression formation occur when information is processed sequentially versus simultaneously. Sequential processing fosters a step-by-step understanding and an impression formation of each piece of information. The impression made on the first information can influence how the second information is processed. In contrast, simultaneous processing enables decision-makers to form an overall impression by information combination (Bazerman et al. 1999; Hoffman, Kagel, and Levin 2011; Jonas et al. 2001; Liu and Wickens 1992; Wickens and Carswell 1995). According to Wickens and Carswell (1995), low separation supports simultaneous processing as it reduces the cognitive demand required to combine information. Since prior research indicates that impression formation is not only influenced by information separation but also by information order (Haugtvedt and Wegener 1994; Hellmann, Yeow, and De Mello 2017; Huang et al. 2014; Kwak and Huettel 2018; Moore

1999; Rey et al. 2020), it is crucial to examine the interactive effects of information separation and information order. This will contribute to a better understanding of the effective provision of market and product information to support idea selection.

Market information provides insights into the market potential of new ideas by customers' opinions (Cui and Xiao 2019; Griffin and Hauser 1993; Parry and Song 2010). Product information provides the necessary background to understand how customers can benefit from it and gives an intuition of its quality and feasibility. This helps to make sense of the customers' opinions. Thus, product information forms the basis for interpreting market information by providing context (Dougherty 1992b; Netz 2017; Ozer 2009; Payne, Frow, and Eggert 2017).

First, I develop theory to predict that decision performance increases under market-first when separation is low compared to high. Combining various information is cognitively demanding (Rinne et al. 2000; Seeber 2011). However, according to prior research, low separation can reduce cognitive demand, which increases the likelihood of combining information (Hilbig et al. 2015; Liu and Wickens 1992; Wickens and Carswell 1995). As a result, market information is more likely understood and interpreted in the context of product information. This leads to more holistic impression formation and enables effective interpretation of market information, resulting in higher performance when separation is low than high under market-first (Huang 2018; Payne, Frow, and Eggert 2017; Wickens and Carswell 1995; Zeng et al. 2018).

Second, I predict that the positive effect of low separation on decision performance is weaker under product-first compared to market-first. The two approaches, market-first versus product-first, differ in terms of the interpretability of the first information. In contrast to market-first, decision-makers can interpret the first information (product) more independently from the second information (market) (Marsh and Stock 2006; Netz 2017; Sukhov et al. 2021). Thus, decision-makers do not have an immediate need for information combination under product-first. This reduces the likelihood of information combination, resulting in a less holistic impression formation (Anderson 1971; Hsee et al. 1999; Weick, Sutcliffe, and Obstfeld 2005). The higher interpretability of the first information weakens the positive effect of low separation on decision performance due to a lower likelihood of information combination under product-first (Huang 2018; Payne, Frow, and Eggert 2017; Wickens and Carswell 1995).

To test my hypotheses, I conduct a 2×2 between-participants online experiment on Prolific. Participants take over the role of a product manager in a firm specializing in app development. All participants receive product and market information on three new app ideas. Participants are responsible for the final idea selection based on the information provided. I manipulate information separation by providing product and market information with or without a time gap. Under high separation, participants receive the first information directly, but the second information is only made available after some time. Under low separation, both pieces of information are provided simultaneously without any time gap. Information order is manipulated by providing first market information (market-first) or product information (product-first).

The market information presented in the experiment is derived from a self-designed survey previously conducted on Amazon Mechanical Turk. In the customer feedback study, participants evaluate various apps across indicators and indicate their willingness to pay, representing the market potential of the apps (Breidert, Hahsler, and Reutterer 2006; Wertenbroch and Skiera 2002). Collecting market information has several advantages compared to a decision-making experiment with a hypothetical scenario. The participants in the experiment are compensated based on the market potential of their selected apps. This allows me to create real economic incentives for the experimental task and to design an experiment with an economic optimum. In addition, I can objectively measure decision performance.

Overall, the results are in line with my hypotheses. I show that information separation and order interactively influence decision performance. Consistent with my predictions, I find that decision performance increases when separation is low compared to high under market-first. In addition, I find that the positive effect of low separation on decision performance is weaker under product-first compared to market-first.

This study makes several contributions to research. My results emphasize the importance of considering the interactive dynamics of information separation and information order. Prior research states that information combination increases under low compared to high separation, which improves decision performance (Bazerman et al. 1999; Hilbig et al. 2015; Liu and Wickens 1992; Wickens and Carswell 1995). My study provides a more nuanced view of the positive effect of low separation on decision performance by showing that this effect is influenced by information order. A higher interpretability of the first information mitigates the positive effect of low separation on information combination since there is less need for combining information. Additionally, I contribute by providing a method that increases external validity and allows to set real financial incentives for the decision task more comparable to the financial incentives in practice. Therefore, I pre-collect market data through a self-designed survey instead of designing a hypothetical decision-making scenario.

My findings are also relevant to practice. Compared to previous research that focuses on the type of information used in idea selection (Hart et al. 2003; Martinsuo and Poskela 2011; Parry and Song 2010; Tzokas, Hultink, and Hart 2004), I show that not only the type of information is critical for effective decision making in idea selection, but also how the information is provided to decision-makers. I contribute to a better understanding of effective information provision regarding the time gap between product and market information by considering the innovation approaches adopted by firms. While firms with a market-first approach should wait until both pieces of information are made available or require the departments to made them simultaneously available for combined reporting, i.e., with low separation, firms with a product-first approach can provide information at the time it is made available by the departments, i.e., with high separation.

II. Theory and Hypothesis Development

Background

Innovation is a key driver for the future success of firms. Therefore, firms strive to constantly generate new ideas to satisfy new customer needs or to enter new markets (Cooper 2013; Hammedi, van Riel, and Sasovova 2011; Markham 2013; Sukhov et al. 2021). Because developing new ideas is resource-intensive and costly, top management has to select those new ideas with the highest market potential to allocate the limited innovation resources efficiently (Berg 2016; Dziallas 2020). Therefore, firms integrate «go/no-go decisions» on new product ideas throughout the innovation process (Cooper 2008; Schmidt, Sarangee, and Montoya 2009; Tzokas, Hultink, and Hart 2004). When making these decisions, top management should select ideas that are worth investing more in and terminate those with lower success potential.

Decision-makers responsible for idea selections, such as top management, are often not directly affiliated with the departments that generate and report essential information for idea selection. In this case, firms need to ensure the accessibility and provision of information to top management (Adams, Day, and Dougherty 1998; Cui and Xiao 2019; Kruft et al. 2019). Given that various information is generated and prepared for reporting by different departments at different times (Dougherty 1992a; Hart et al. 2003; Tzokas, Hultink, and Hart 2004), firms face the challenge of how information should be provided to top management for idea selection. Either firms provide information as soon it is made available for reporting (high separation) or combine all information in one report before providing it (low separation).

For innovation, firms adopt either a more product-oriented or market-oriented approach. Under a product-oriented approach, the innovation process is organized around the product, prioritizing the utilization of internal resources and the exploitation of technological competencies. In contrast, under a market-oriented approach, firms center innovation effort around customers, placing a stronger emphasis on collecting and disseminating market insights (Gatignon and Xuereb 1997; Homburg and Pflesser 2000; Kohli and Jaworski 1990; Parry and Song

2010). The two innovation approaches imply that the initial steps in the innovation process and the corresponding decisions are driven either more by product information (hereafter: product-first) or market information (hereafter: market-first). This affects the order in which product and market information is disseminated to top management. Depending on the approach, firms disseminate either product or market information as early as possible compared to the other information. This means that under product-first, product information is disseminated earlier to inform top management first about technical components and feasibility. Under market-first, market information is disseminated earlier to inform top management first about customers and their opinions (Cui and Xiao 2019; MacCormack and Verganti 2003; Spanjol, Qualls, and Rosa 2011; Zahay, Griffin, and Fredericks 2011).[9]

Previous research shows that product and market information are both essential for effective idea selection (Martinsuo and Poskela 2011; Parry and Song 2010; Payne, Frow, and Eggert 2017; Tzokas, Hultink, and Hart 2004). While product information describes the new idea and its features, market information informs about the market potential based on customers' opinions (Cui and Xiao 2019; Griffin and Hauser 1993; Parry and Song 2010). Product information ensures that decision-makers can comprehend the potential benefits a new idea offers based on its features and provides an intuition of quality and feasibility. An intuitive understanding of the features and benefits supports decision-makers sense-making of market information. By understanding how customers can benefit from a new idea, decision-makers can better interpret why customers evaluate the new idea as they did. Thus, product information provides the basis for interpreting market information by giving context (Dougherty 1990; 1992b; Netz 2017; Ozer 2009; Payne, Frow, and Eggert 2017).

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[9] For example, the R&D department develops a prototype that is used by the marketing department for customer feedback. Under product-first, firms focus on the early dissemination of product information. Therefore, the R&D departments prepare a report by detailing the product's features and benefits before the market information is disseminated. In contrast, under market-first, the R&D department shares knowledge about the product features within the department by designing the prototype. But at the time the marketing department reports the results from the customer feedback (being the starting point for innovation), the detailed product information is not yet reported to top management. Thus, the order in which information is disseminated to top management differs between the two approaches, even though the information may be shared already within a department.

Effect of information separation under market-first

I first predict that a low separation supports information combination and the formation of a holistic impression, which improves decision performance under market-first. Combining information for an integrative interpretation is cognitively demanding (Rinne et al. 2000; Seeber 2011). However, low separation can reduce cognitive demand, which increases the likelihood that decision-makers will combine information more likely when separation is low compared to high. Prior research indicates that decision-making improves when information is provided in closer proximity, as fewer cognitive resources are needed to combine various pieces of information (Bazerman et al. 1999; Chandler and Sweller 1991; Hilbig et al. 2015; Liu and Wickens 1992; Wickens and Carswell 1995).

A low separation increases the likelihood that both types of information are combined (Bazerman et al. 1999; Hilbig et al. 2015). This implies that under market-first, decision-makers are more likely to form an impression of the market information in relation to their product understanding. Product information provides decision-makers with the necessary context and an intuitive framework in which the market information is more effectively understood, interpreted, and evaluated (Dougherty 1990; 1992b; Netz 2017; Ozer 2009; Payne, Frow, and Eggert 2017). This results in a more holistic impression formation and improves decision performance under low separation compared to high separation (Huang 2018; Payne, Frow, and Eggert 2017; Wickens and Carswell 1995; Zeng et al. 2018).

In contrast, the cognitive demand for combining information is more pronounced under high separation, as more cognitive capacity is required to combine information. Consequently, providing information with high separation leads decision-makers to process information more independently from each other instead of combining information for holistic impression formation (Liu and Wickens 1992; Wickens and Carswell 1995). Under market-first, the market information is interpreted first without knowledge of the product information. Thus, when information separation is high, effective information processing is more likely impaired as the context provided by the product information, which is needed for an effective interpretation of market information, is missing (Dougherty 1990; 1992b; Payne, Frow, and Eggert 2017).

When separation is high, it is also less likely that the initially interpreted market information is reinterpreted after the product information becomes available. Decision-makers are more likely to process the information sequentially due to the lower cognitive demand needed (Chandler and Sweller 1991; Kool et al. 2010; Liu and Wickens 1992; Wickens and Carswell 1995). Under market-first, decision-makers form an impression about the market without understanding the product features and benefits when the separation is high. This reduces the ability to make sense of market information and consequently reduces decision performance (Huang 2018; Payne, Frow, and Eggert 2017; Wickens and Carswell 1995; Zeng et al. 2018).

To summarize, under market-first, the information needs to be provided in a way that supports information combination for a more effective interpretation of the market information. When separation is low under market-first, the market information is more likely interpreted in the context of product information, which in turn improves decision performance. Thus, I predict that under market-first, decision performance increases under low compared to high separation due to a greater likelihood of information combination under low separation.

> *H1: Under market-first, decision performance increases when separation is low compared to high.*

Interactive effect of information separation and information order

According to prior research, low separation reduces the cognitive demand required to combine information, increasing the likelihood of information combination (Hilbig et al. 2015; Liu and Wickens 1992; Wickens and Carswell 1995). However, I predict that the likelihood of information combination also depends on information order (Anderson 1971; Hsee et al. 1999; Savolainen 2017; Weick, Sutcliffe, and Obstfeld 2005).

Under market-first, decision-makers have a stronger need to combine other information to improve their understanding of the market information (Anderson 1971; Bazerman et al. 1999; Dougherty 1990; 1992b; Payne, Frow, and Eggert 2017; Weick, Sutcliffe, and Obstfeld 2005; Zeng et al. 2018). Low separation is particularly beneficial in this case as it supports decision-makers in their information combination by reducing cognitive demand (Hilbig et al. 2015; Liu and Wickens 1992; Wickens and Carswell 1995). When separation is low, decision-makers combine both pieces of information more likely to gain background information on new ideas' features and benefits to support their sensemaking of the market information (Dougherty 1990; 1992b; Payne, Frow, and Eggert 2017).

In contrast, under product-first, decision-makers do not have an immediate need to combine information as the first information (product) is easier to interpret more independently from the second information (market) (Marsh and Stock 2006; Netz 2017; Sukhov et al. 2021). Decision-makers do not need to integrate the market information to improve their understanding of the product information (Anderson 1971; Hsee et al. 1999; Savolainen 2017; Weick, Sutcliffe, and Obstfeld 2005). Thus, even if separation is low, I expect that under product-first, decision-makers first process the product information and then the market information, as this is less cognitively demanding than combining information (Chandler and Sweller 1991; Kool et al. 2010; Liu and Wickens 1992; Wickens and Carswell 1995). In contrast to market-first, the easier interpretability of the first information under product-first reduces the likelihood of combining information. This weakens the effect of low separation on decision performance under product-first (Huang 2018; Payne, Frow, and Eggert 2017; Wickens and Carswell 1995).

H2: The positive effect of low separation on performance is weaker under product-first than under market-first.

III. Method

Experimental design and task

To test my hypotheses, I conduct a 2 × 2 between-subjects experiment. Two factors are manipulated: (1) information separation (*low vs. high*) and (2) information order (*product-first vs. market-first*).[10] The experiment spans five periods. Thus, period is a within-subjects factor. To control for order effects, the order of the three app presentations was counterbalanced, resulting in three groups per condition.[11]

For the study, participants take over the role of a product manager in a company specializing in app development. In each condition, participants review both product and market information to make idea selection decisions. In each of the five periods, all participants receive product and market information about three new app ideas. Participants are informed that both types of information are important for idea selection. Participants are responsible for selecting one app of the three apps presented based on the information provided.

Experimental manipulations

I first manipulate whether participants receive product and market information with high or low information separation. High separation means that the participants receive the first information at the beginning of each period and are required to assess this information for at least 60 seconds before they can access the second information. The next button is only accessible after 60 seconds to prevent participants from directly assessing the second information. This design choice reflects the time gap decision-makers experience when information separation is high, i.e., when there is a time gap between providing the two pieces of information.

[10] The experiment was approved by the ethics committee of the university the author is affiliated with.

[11] I use random orders of the low, medium and high WTP app in each group and period. Thus, the app with the high WTP is always positioned at another place in each group per period (see Appendix). All statistical inferences about the hypothesis tests remain the same when I control for order effects of app presentation and period. Therefore, I do not consider order and period in the following.

In practice, this time gap is likely longer. However, to test my hypotheses, the length of the time gap is of less importance. What is more important is that the decision-makers process the first information separately from the second. Thus, the decision-makers have already processed the first information and already formed an impression before the second information is made available.[12] In contrast, in the low information separation condition, participants have direct access to both information simultaneously without any time gap.[13]

Second, I manipulate whether market information (*market-first*) or product information (*product-first*) is provided first.[14] In case of high separation, one information was provided first, and the other information was provided no earlier than 60 seconds later. In case of low separation, either market information or product information was presented at the top of the page, followed by the other information below. I present the experimental design in the Appendix.

Product and market information – Pre-Study

The market information used in the experiment is derived from five self-designed surveys on customer feedback previously conducted on Amazon Mechanical Turk (see: essay 1). In each survey, participants evaluate five apps from the same domain (travel, workout, nutrition, friends, delivery). For example, if participants take part in the customer survey on workout apps, they receive five workout apps. For the surveys I developed app ideas and designed a presentation for each app containing a picture of the app and a description of its features.

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[12] After participants have processed the first information for at least 60 seconds, they are able to navigate back and forth between the two pieces of information. Only 15% of participants in the experiment navigate back to the first information. This shows that most participants perceive no need to re-process the first information, as they already have internalized the first information, have processed it, and have already formed an impression of it.

[13] In practice, mixed forms can exist along the continuum of separation. However, focusing on the two ends of the continuum is a cleaner way to test my theory in terms of the directional predictions.

[14] My research deals with product information in terms of updating decision-makers on new ideas, their features, and benefits, which is usually more qualitative, while market information is usually more quantitative by providing information on the mean values of customer evaluations. Thus, the information in my experiment represents the usual format in practice to analyze my theory in the most realistic setting possible. Based on theory, it can be assumed that my directional predictions still hold. Qualitative market information would decrease the interpretability of first information under market-first, leading to a stronger need to combine information and consequently to a positive effect of low separation on decision performance. Quantitative product information should still be easier to interpret without market information. Thus, decision-makers do not have an immediate need to combine information, leading also to a weaker effect of low separation on decision performance under product-first.

In the study, participants receive first an app presentation and have to familiarize themselves with the app idea. Then, they provide customer feedback by evaluating the app across defined indicators on a 7-point Likert scale. After rating an app, participants move on to the next app presentation and rate it across the ten indicators.[15] In addition to rating the apps, the participants indicate their willingness to pay (WTP) for the apps. Participants always indicate their WTP after rating one app on all indicators. The WTP represents the maximum subscription fee that customers are willing to pay in dollars per month for an app. The WTP indicates the market potential of every app (Breidert, Hahsler, and Reutterer 2006; Wertenbroch and Skiera 2002). After participants had rated all five apps, they provided demographic information.

The pre-collected market data offers advantages for the experiment compared to a typical JDM experiment using a hypothetical scenario. I use the obtained WTP of each app to measure decision performance and to incentivize participants. Specifically, participants who select an app with higher WTP, i.e., higher market potential, receive more performance points and, at the end of the experiment, a higher variable compensation. Each dollar of customers' WTP counts for 100 points, which equates to \$0.001 in compensation. This allows me to create real economic incentives for the idea selection task, comparable to the financial incentives in practice for better idea selection. In addition, it allows me to measure performance objectively.

Product and market information provided in the experiment

I use the app presentations designed for the customer feedback study as product information for the experiment.[16] I select 15 of the 25 apps to increase experimental control regarding app comparability across periods. For the market information indicators and WTP, I refer to a subsample of the customer feedback study that is more likely to represent a realistic target

[15] I present an app example with an excerpt of the questions from the customer feedback study in the Appendix.
[16] I made some minor changes in app descriptions to control for description length in every period. These adjustments only influence description length without changing the description content in terms of apps' objectives.

group to reduce noise. The sample is defined by those MTurk participants who are highly involved in the respective domain, very open to innovation, and generally willing to pay for apps.

Based on the average WTP of the apps, I classify three categories: low WTP ($1.00 - $1.99), medium WTP ($2.00 - $2.99) and high WTP ($3.00 - $3.99).[17] In every period, participants receive a low, a medium, and a high WTP app. Participants are informed that the WTP for apps may vary and that apps, in general, are classified into the three categories. However, they were not informed that every period consists of a low, medium, and high WTP app.

For the experiment, I use the five indicators Usefulness, Interest, Ease of Use, Benefits, and Clearness. In the experiment, the participants receive the means of each indicator based on the ratings of the target group sample. Among the five indicators used for the experiment, Usefulness, Interest, and Benefits are positively associated with the WTP. As such, in each period, the app with the highest WTP consistently demonstrates the highest mean values in Usefulness, Interest, and Benefits compared to the other two apps. To account for the ambiguity of indicators in practice, Clearness and Ease of Use, show lower mean values for the high than for the medium WTP app. This reflects that an increase in each indicator does not necessarily lead to an increase in WTP (Carson, Wu, and Moore 2012).[18] Participants in the experiment were not informed about the directional relations of the indicators, requiring them to recognize which indicators signal a better app. Those who successfully recognize the link between indicators and WTP can achieve higher performance by making better decisions when selecting an app.

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[17] To increase experimental control, I made minor adjustments to the WTP of two (of 15) apps. The difference in the WTP in every period is, therefore, always at least $0.40 between the low and medium WTP app and between the medium and high WTP app. The low WTP range starts at $1.00, as no app has a mean value below $1.00.

[18] The Appendix includes an overview of the five indicators. For Usefulness, Interest, and Benefits the mean value of the high WTP app is always +0.1 or higher than that of the medium WTP app. For Clearness and Ease of Use, the mean value of the high WTP is always -0.1 or lower than that of the medium WTP app. To reduce decision complexity, the low WTP app exhibits lower values in all five indicators than the medium, respective the high WTP app. To keep experimental control, some mean values of the indicators were slightly adjusted in terms of the overall delta thresholds to achieve more consistency across all periods. In line with the directional relations, Usefulness, Interest, and Benefits show a significant positive effect on the desirability and consequently on WTP in the customer feedback study (essay 1), and Clearness a significant negative effect. As Ease of Use relates more logically to Clearness regarding product usage, these two indicators provide a more consistent picture of what customers still do not like about the app, which is the reason why I choose Ease of Use as the fifth indicator. For more information on the customer feedback study, please refer to the first essay in this dissertation.

Dependent variable

The dependent variable *Decision Performance* is measured by a binary variable that equals 1 if the high WTP app is selected and 0 otherwise. To achieve the highest return on innovation development, firms aim to select the idea with the highest WTP across all new ideas in each decision period (Berg 2016; Cooper, Edgett, and Kleinschmidt 2001; Toubia and Florès 2007). Consequently, I focus on the effects of information separation and information order on selecting the high WTP app. To provide further evidence, I also measure participants' average *Performance Points* across all periods. I calculate it by multiplying the customers' willingness to pay for the selected app by 100. It represents participants' decision performance in terms of the market potential of their selected apps.

Procedures and participants

For the experiment, participants were recruited on the web-based crowdsourcing platform Prolific. Participation was restricted to participants living in the U.S., fluent in English, and having a study background in one of the following subjects: Accounting, Business, Communication and/or Media, Economics, Finance, Management, or Marketing. Participants were asked these pre-screening questions again at the beginning of the experiment. Only those who were consistent in their responses to these questions and the information they provided in their Prolific profile were allowed to participate in the experiment.[19]

Participants were randomly assigned to the four experimental conditions. After reading the instructions and taking a quiz to ensure understanding of the instructions, participants began with period 1. In each period, participants first review the product and market information presented in the order and way described above before making a final idea selection decision. After

[19] To ensure high quality participation the pool was also restricted to participants who have an approval rate of 98% or higher and who already had a minimum of 50 submissions on Prolific. Participants are required to pass two attention checks and could only process to period 1 of the experiment when answered both questions correctly (Bentley 2021; Peer et al. 2022).

each period, participants receive feedback on the market potential of their selected app represented by the WTP obtained in the customer feedback study. Upon completing the five periods, participants answer post-experimental questions and provide demographic information.

In total, 236 participants completed the experiment on Prolific. For the final sample, 15 participants were excluded due to duplicated IP to prevent ballot-box stuffing or because they used mobile devices, as the experimental information can only be properly displayed on a computer or laptop. In addition, 21 participants who failed at least one of two manipulation checks were excluded. The first manipulation check required participants to specify the order in which they saw the information by asking which of the two pieces of information they saw first – product or market information. The second manipulation check asked participants whether the product and market information were on the same page or two separate pages, aiming to assess their attentiveness to information separation. The final sample consists of 200 participants.

Participants completing the experiment receive a fixed pay of £3.40 and a variable pay depending on their decision performance in every period. On average, participants receive a variable pay of £1.34 and complete the experiment in 25 minutes. The final compensation (sum of fixed and variable pay) represents, on average, a high hourly payment rate on Prolific.[20] Participants in the final sample are, on average, 28 years old, and the majority studied for two years. The majority achieved an undergraduate degree as the highest education level. Participants have, on average, two years of marketing, one and a half years of research and development, and one and a half years of product manager experience.

[20] Prolific requires a minimum hourly rate of £6.00 and recommends £9.00 (Prolific 2024). The hourly rate in my experiment varies between £10.15 and £11.64, depending on the variable pay between £0.83 and £1.45.

IV. Results

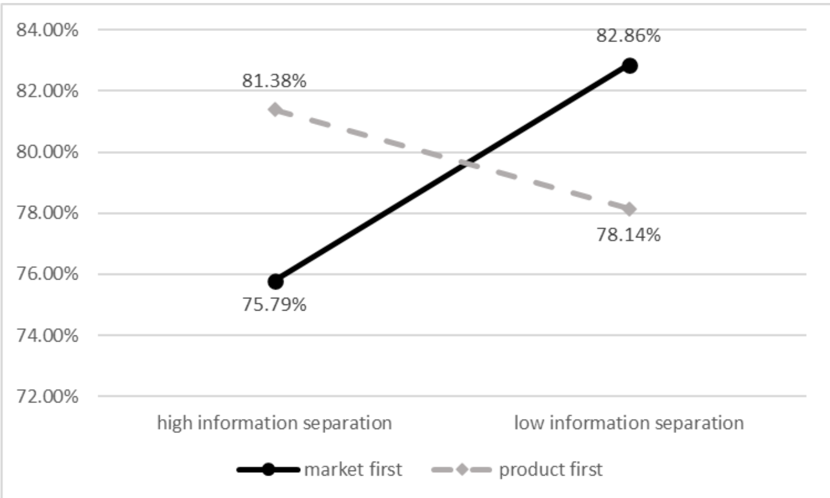
Descriptive Statistics

Figure 1 illustrates the pattern of the variables *Decision Performance* and *Performance Points*. Table 1 Panel A reports the proportion of cases when the high WTP app is selected across conditions. It shows that under market-first, the percentage of selecting the high WTP app increases when information separation is low compared to high (82.86% vs. 75.79%). Under product-first, the percentage of selecting the high WTP app increases to a lesser extent and, in fact, even decreases slightly from low to high separation (78.14% vs. 81.38%). These descriptives provide initial evidence in line with my hypotheses.

Table 1 Panel B presents descriptive statistics for the average performance points across experimental conditions. It shows mean values and standard deviations. Under market-first, the performance points increase when information separation is low compared to high (331.57 vs. 324.78). In addition, the descriptives reveal that under product-first, the performance points are higher when the separation is high compared to low (330.69 vs. 324.04).

FIGURE 1
Pattern

Decision Performance



Performance Points

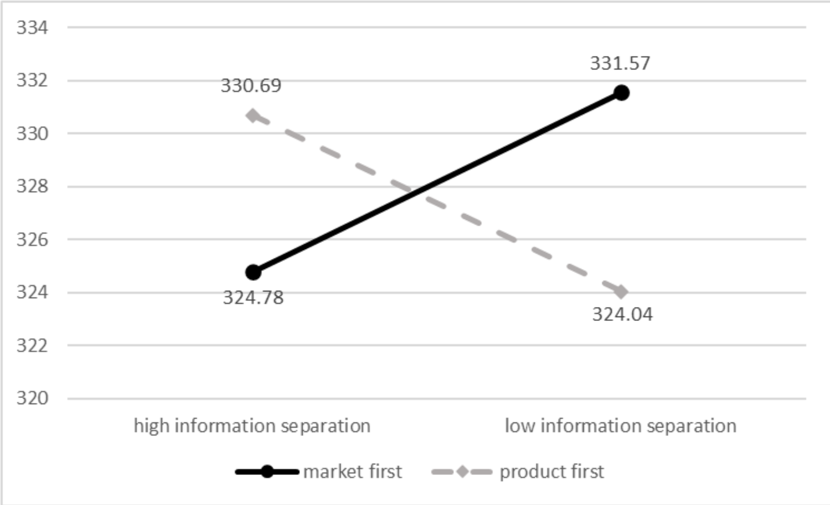


Figure 1a graphically presents the mean values for the dependent variable *Decision Performance* across all experimental conditions. The dependent variable is defined by a binary variable that equals to 1 if the high WTP app is selected and 0 otherwise. Figure 1b graphically presents the mean values of the variable *Performance Points* which is calculated by the willingness to pay for the selected app in each period multiplied by 100.

TABLE 1
Decision Performance

Panel A: Descriptive statistics – Percentage of selecting high WTP app

	High WTP app not selected	*High WTP app selected*	*Total*
Market-first – High separation	24.21% n=69	75.79% n=216	100.00% n=285
Market-first – Low separation	17.14% n=36	82.86% n=174	100.00% n=210
Product-first – High separation	18.62% n=54	81.38% n=236	100.00% n=290
Product-first – Low separation	21.86% n=47	78.14% n=168	100.00% n=215
Total	20.60% n=206	79.40% n=794	100.00% n=1000

Panel B: Descriptive statistics – Mean (standard deviation) performance points

	High separation	*Low separation*	*Both*
Market-first	324.78 (54.89) n=285	331.57 (52.40) n=210	327.66 (53.90) n=495
Product-first	330.69 (53.11) n=290	324.04 (57.81) n=215	327.86 (55.20) n=505
Both	327.76 (54.04) n=575	327.76 (55.26) n=425	327.76 (54.53) n=1000

Table 1 Panel A displays the percentage of cases when the high app is selected across all experimental conditions. Panel B displays the mean values for the performance points across all experimental conditions. It is calculated by the willingness to pay for the selected app in each period multiplied by 100. Conducting five periods in the experiment results in a total of 1000 observations from a total of 200 participants.

Hypotheses Test

To test my hypotheses, I use a logit regression to regress *Decision Performance* on *Low Separation* (equals to 1 if low and 0 if high), *Product-first* (equals to 1 if product-first and 0 if market-first), and the interaction of the two variables. Standard errors are clustered at the participant level to account for multiple observations within participants. *Decision Performance* is determined by the binary variable that equals to 1 if the high WTP app is selected and 0 otherwise. The results are reported in Table 2.[21]

H1 predicts that the decision performance under market-first increases when information separation is low compared to high. H2 predicts that this positive effect is weaker under product-first than under market-first. Consistent with H1, the coefficient of *Low Separation*, reflecting the simple effect of low versus high separation under market-first, i.e., when *Product-first* equals to 0, is significant and positive (Model 1: $\beta = 0.43$, $p = 0.05$).[22] Thus, decision

[21] All statistical inferences of the hypothesis tests remain the same when I control for order effects of app presentation and period effects. The reported models are run and presented without order and period as control variables.
[22] P-levels in this section are one-tailed for directional expectations and two-tailed otherwise.

performance increases significantly under market-first when separation is low compared to high. Additionally, the regression reveals a negative and significant interaction term (Model 1: $\beta = -0.64$, $p = 0.08$), supporting H2. This shows that the effect of low versus high separation is significantly weaker under product-first compared to market-first. The simple effect of low separation versus high separation under product-first is negative but insignificant (Model 1: $\beta = -0.21$, $p = 0.441$). This indicates that decision performance does not differ between low and high separation under product-first. To provide further evidence, in Model 2, I rerun the regression with *Performance Points* as the dependent variable in an OLS regression. All inferences for the hypotheses test remain the same (Model 2: H1: $\beta = 6.79$, $p = 0.08$; H2: $\beta = -13.45$, $p = 0.05$; simple effect product-first: $\beta = -6.66$, $p = 0.162$).

TABLE 2
Decision Performance

Effect of Low Separation and Product-first on Decision Performance

	Model 1	Model 2	Model 3	Model 4
Constant	1.14 (0.18) p<0.001***	324.78 (3.58) p<0.001***	0.72 (0.28) p=0.01***	312.36 (6.85) p<0.001***
Low Separation	0.43 (0.26) p=0.05**	6.79 (4.73) p=0.08*	0.89 (0.38) p=0.01***	23.27 (7.64) p=0.002***
Product-first	0.33 (0.26) p=0.195	5.91 (4.66) p=0.206	0.88 (0.44) p=0.05**	21.11 (8.38) p=0.014**
Low Separation * Product-first	-0.64 (0.37) p=0.08*	-13.45 (6.70) p=0.05**	-1.41 (0.58) p=0.02**	-35.47 (11.17) p=0.002***
Simple effect of Low Separation when Product-first is 0 (*market-first*)	0.43 p=0.05**	6.79 p=0.08*	0.89 p=0.01***	23.27 p=0.002***

Simple effect of Low Separation when Product-first is 1 (*product-first*)	-0.21 p=0.441	-6.66 p=0.162	-0.52 p=0.236	-12.20 p=0.139
R^2	0.005	0.004	0.03	0.03
N	1000	1000	350	350

Table 2 presents the regression of *Decision Performance* on *Low Separation* (equals to 1 if information separation is low and 0 if high), the *Product-first* (equals to 1 if product-first and 0 if market-first) and the interaction of the two variables. In Model 1 *Decision Performance* is determined by the binary variable that equals to 1 if the high WTP app is selected and 0 otherwise. Model 1 is run by a logit regression. In Model 2 the dependent variable is determined by *Performance Points*, i.e. by the willingness to pay for the selected app multiplied by 100. In Model 3 (binary DV) and Model 4 (continuous DV), I rerun the regression of the main analysis with the subsample of experienced participants. The subsample represents those participants with at least one year of product manager experience. Standard errors are clustered at participant level to account for multiple observations within participants (total of participants: 200 in Model 1 and 2 and 70 in Model 3 and Model 4). * p ≤ 0.10; ** p ≤ 0.05; *** p ≤ 0.01; p-levels are one-tailed for directional predictions and two-tailed otherwise.

Supplemental Analyses

Product Manager Experience

Idea selection is typically executed by experienced managers (Berg 2016; Sukhov et al. 2021). It can be assumed that professional experience can lead to more rational information processing reducing biases. Thus, I test the effects of information separation and information order on decision performance for the subsample of participants with product manager experience of at least one year. To test this, I rerun regression models 1 and 2 of the hypotheses test with the subsample of experienced participants. The results are reported in Table 2. The coefficient of *Low Separation* is significant and positive (Model 3: β = 0.89, p = 0.01; Model 4: β = 23.27, p = 0.002).[23] The interaction term is significant and negative (Model 3: β = -1.41, p = 0.02; Model 4: β = -35.47, p = 0.002). The simple effect of low separation versus high separation under product-first is negative and insignificant (Model 3: β = -0.52, p = 0.236; Model 4: β = -12.20, p = 0.139). The results show that the directional effects remain equal but that the p-values are smaller for the subsample of experienced participants compared to the full

[23] P-levels in this section are one-tailed for directional expectations and two-tailed otherwise.

sample. Thus, the effects are even stronger for experienced participants. Consequently, professional experience does not mitigate but rather intensifies the biases in information processing.

Likelihood of Information Combination

In the theory development, I argue that under market-first, the likelihood of information combination increases when separation is low compared to high. The underlying reason is that low separation reduces the cognitive demand for information combination (Hilbig et al. 2015; Liu and Wickens 1992; Wickens and Carswell 1995). In addition, I argue that the positive effect of low separation on information combination is weaker under product-first compared to market-first. Decision-makers under product-first have less likely an immediate need for information combination. In contrast to market-first, under product-first, the first information (product) is easier to interpret independently from the second information (market). This reduces the likelihood that decision-makers combine both pieces of information under product-first, even when separation is low (Anderson 1971; Hsee et al. 1999; Marsh and Stock 2006; Netz 2017; Sukhov et al. 2021; Weick, Sutcliffe, and Obstfeld 2005).

To provide further evidence on the likelihood of information combination, I analyze the effect of low separation on it under market-first and product-first. I measure the dependent variable *Information Combination* by asking to what extent participants agree that they are able to combine product and market information to make a final decision. I measure *Information Combination* as a post-experiment question on a 7-point Likert Scale. The independent variable *Low Separation* equals to 1 if low and 0 if high. I run two regressions to analyze how low separation affects the likelihood of information combination under each approach. Table 3 reports the results under market-first (Model 1), and under product-first (Modul 2).

The regression analysis of *Information Combination* on *Low Separation* under market-first shows a significant positive coefficient (Model 1: $\beta = 0.29$, $p = 0.09$ one-tailed). In contrast, the regression analysis of *Information Combination* on *Low Separation* under product-first shows an insignificant and slightly negative coefficient (Model 2: $\beta = -0.01$, $p = 0.941$ two-tailed). Both results are in line with my underlying theory. While low separation increases the likelihood of information combination under market-first, this likelihood does not differ between low and high separation under product-first.

The two approaches, market-first and product-first, differ in the interpretability of the first information. While market information interpretation requires context and thus knowledge of the product information, product information can typically be interpreted more independently from market information (Dougherty 1990; 1992b; Marsh and Stock 2006; Netz 2017; Ozer 2009). This analysis shows that the positive effect of low separation on information combination varies under market-first compared to product-first. Therefore, the likelihood of combining information depends not only on information separation but is contingent on the interpretability of the first information and, consequently, on information order.

TABLE 3
Information Combination

Effect of Low Separation on Information Combination

	Model 1	Model 2
Constant	6.16 (0.14) p<0.001***	6.22 (0.13) p<0.001***
Low Separation	0.29 (0.22) p=0.09*	-0.01 (0.20) p=0.941
Adjusted-R^2	0.008	-0.01
N	99	101

Table 3 presents the regressions of *Information Combination* on *Low Separation* under market-first (Model 1) and product-first (Model 2). I measure the dependent variable *Information Combination* in a post-experimental questionnaire, asking participants about their agreement with the following statement: «I was able to combine the app description and the market data very well to make a final decision». The variable is measured on a 7-Point Likert-Scale. The independent variable *Low Separation* equals to 1 if low and 0 if high. * $p \leq 0.10$; ** $p \leq 0.05$; *** $p \leq 0.01$; p-levels are one-tailed for directional predictions and two-tailed otherwise.

V. Conclusion

In this paper, I investigate how information separation and information order affect decision performance in idea selection. Using an experiment, I show that the performance increases when information separation is low compared to high under market-first. I also show that this positive effect is weaker under product-first. With a supplemental analysis, I reveal the reason behind. Under market-first, information combination increases with low separation compared to high separation. In contrast, this effect is insignificant under product-first, i.e. there is no significant difference in information combination between low versus high separation.

To test my hypothesis, I design an experiment using real market information, which has several advantages. First, collecting market information regarding customer opinions and WTP increases the external validity of the decision task in the experiment. Second, as participants are compensated based on the WTP of selected products, I can set real economic incentives. Third, it allows me to measure the dependent variable objectively.

I contribute to the literature by showing a more nuanced view of the effect of information separation on information combination and decision performance. Prior research states that information combination increases under a low compared to a high separation. My research also emphasizes that the interpretability of the first information and therewith the information order influence whether information is more likely combined or not. Based on theory, low separation decreases the cognitive demand for combining information and thus increases the likelihood of information combination. My study shows that the positive effect of low separation on information combination is weaker when decision-makers lack a need to combine information. The easier the first information is interpretable independently from the second information, the less likely decision-makers are to combine information lacking the need to do so. The results have also implications for practice. While firms with a market-first approach should provide product and market information in a way that supports information combination, i.e., with low separation, firms with a product-first approach can provide them with high separation.

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Appendix

Excerpt of customer feedback study on MTurk

Track the accuracy of your exercise execution

Follow the video instructions of a workout.


Track how accurately you execute every exercise by video filming yourself. The app will automatically detect correct and incorrect executions and display green and red lines accordingly. Additionally, you will receive real-time cues so that you can correct and improve your execution.

------------------------------------ Page Break ------------------------------------

What is **your impression of the app** in terms of the **following criteria**?

	1	2	3	4	5	6	7	
The app is **very useless**	○	○	○	○	○	○	○	The app is **very useful**
The app is **very boring**	○	○	○	○	○	○	○	The app is **very interesting**
The app is of **very low quality**	○	○	○	○	○	○	○	The app is of **very high quality**
The app is **very unexciting**	○	○	○	○	○	○	○	The app is **very exciting**
The app **looks very unappealing**	○	○	○	○	○	○	○	The app **looks very appealing**

Overview of indicators used in the experiment

Indicator	Question asked in the Pre-Study	7-Likert Scale
Usefulness	What is the impression of the app in terms of the following criteria?	The app is very useless to the app is very useful
Interest	What is the impression of the app in terms of the following criteria?	The app is very boring to the app is very interesting
Ease of Use	I would find the app easy to use.	Strongly disagree to strongly agree
Benefits	To what extent can the app add benefits for you?	The app adds no benefits at all to the app adds lots of benefits
Clearness	It is clear and understandable how to use the app.	Strongly disagree to strongly agree

Period 1: product-first | separation high

App Descriptions

App 1: DamageReport

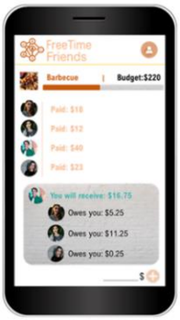
Do not worry about damaged items from deliveries

Upload photos of the delivered items and damages.

Name the online store from which you purchased the items. Select your preferred solution, such as an item exchange or payment refund, and your preferred time and address for pick-up of the damaged items by our staff.

After submission, we take care of the damage report and the return of the damaged items. In addition, we take care of the communication with the company and keep you informed about the status of the exchange or refund.

App 2: SharedExpenses



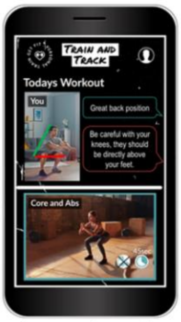
Manage shared expenses with your friends

Set a budget for an event.

Add your payments and track everyone's spending.

Based on everyone's spending, the app automatically calculates how much you have to pay to whom or how much someone owes you, and gives you a corresponding overview. Your friends get their own overviews, so everyone can easily manage their costs.

App 3: Train&Track



Track the accuracy of your exercise execution

Follow the video instructions of a workout.

Track how accurately you execute every exercise by video filming yourself. The app will automatically detect correct and incorrect executions and display green and red lines accordingly.

Additionally, you will receive real-time cues so that you can correct and improve your execution.

Market Data →

------------------------------------ Page Break ------------------------------------

Market Data

App 1: DamageReport

Average customer opinion:

App 2: SharedExpenses

Average customer opinion:

App 3: Train&Track

Average customer opinion:

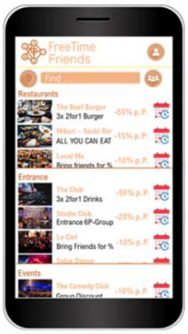
← App Description

End of Report →

Period 2: product-first | separation low

App Descriptions and Market Data

App 1: GroupDiscounts



Get discounts for you and your friends

Enter a location where you want to find a restaurant, club or event with your group and specify the size of your group.

-50% p.P. The app displays discounts for restaurants, club entrances, and events at the specified location and for the specified group size. Click on the discount to receive further information.

Get a discount by booking a table or tickets directly in the app.

Average customer opinion:

App 2: PerfectTour

See the most with the most suitable sightseeing route

Search for a city. Swipe through the images of interesting locations in the chosen city. Like or dislike each location to narrow down your search to locations you want to visit.

Enter the time you have available in the chosen city. Based on your available time and the locations you want to visit, the most suitable sightseeing route will be automatically displayed.

--h --min The app will guide you and send you a reminder when you need to leave one location to visit the next one. At every location you can decide to walk to the next location or to use public transport.

Average customer opinion:

App 3: NutriCommunity

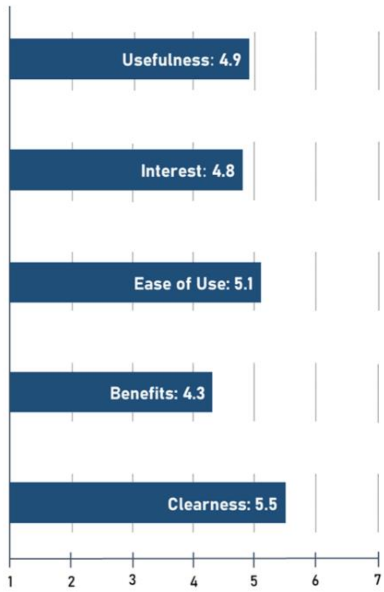
Find support from communities of people who share the same diet

DIET ONLY Select which foods you would like to eat and those you do not eat, and define whether this is for diet reasons or due to food intolerance.

The app will recommend communities of people who share the same diet as you.

As a community member, you can interact with other members to get support and advice. You can read blog posts and recipes from other community members, share your own blog posts and recipes, or engage in private chats.

Average customer opinion:



End of Report →

Period 3: market-first | separation high

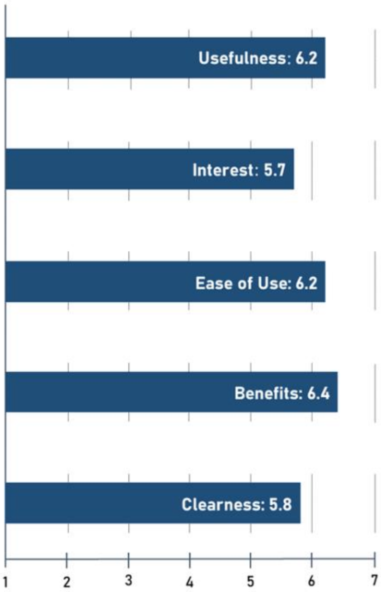
Market Data

App 1: LuggageStorage

Average customer opinion:

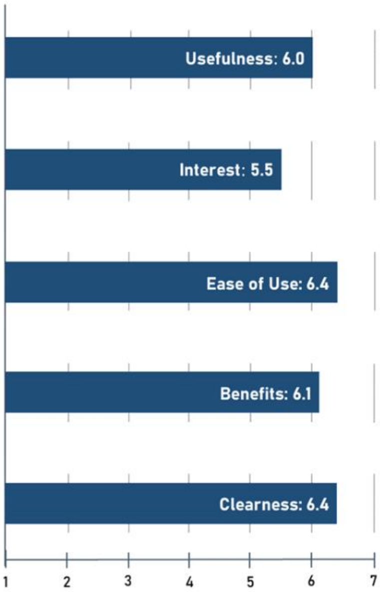
App 2: RestaurantFinder

Average customer opinion:



App 3: OrderOverview

Average customer opinion:



App Description →

------------------------------------ Page Break ------------------------------------

App Descriptions

App 1: LuggageStorage

Store your luggage safely during a city trip

Enter your current location. Select then one of the displayed storage locations.

Receive information about the storage prices and operating hours.

Receive up-to-date information about the travel time to get to the selected storage location and times from the selected storage location to the central station and airport.

After booking the storage for a certain time in the app, the remaining time until luggage pick-up is displayed.

App 2: RestaurantFinder

Find restaurants offering meals that fit your diet

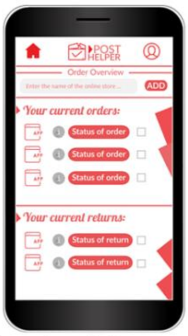
Select which foods you would like to eat and those you do not eat, and define whether this is for diet reasons or due to food intolerance.

Select the city where you want to find a restaurant and which type of meal you prefer.

The app automatically scans the menus of all restaurant websites in your selected city and displays those restaurants offering meals that fit your diet.

Get an easy overview of the restaurant menus and save your favorites. Book a table directly in the app or order your food by delivery.

App 3: OrderOverview



Keep track of all your orders and returns

Search for all the online stores you have recently ordered items from and add your orders to the list in the app.

Through in-app integration, all your orders and returns will be automatically transferred into the app and will be displayed.

Stay informed about all your orders and returns you currently have and check your delivery and return status.

After the order is delivered or returned it will be deleted from the list.

← Market Data

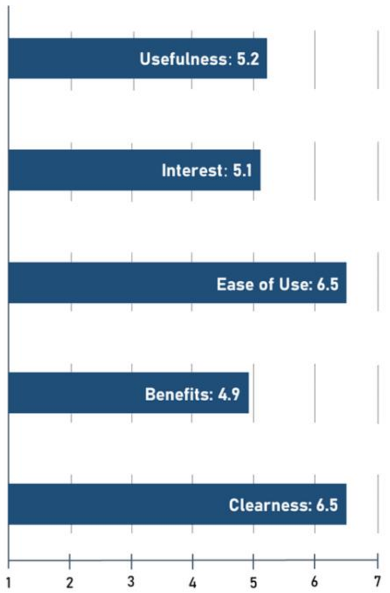
End of Report →

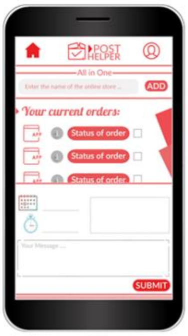
Period 4: market-first | separation low

Market Data and App Descriptions

App 1: All-in-One

Average customer opinion:





Bundle all your orders into one delivery

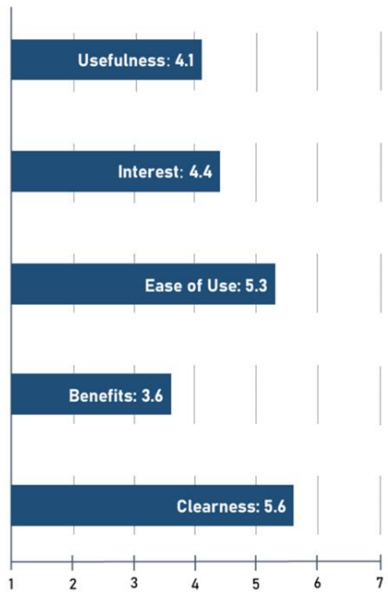
ADD Search for all the online stores you have recently ordered items from and add your orders to the list in the app.

Through in-app integration, information from your orders will be automatically transferred into the app. So you get an overview of all ordered items and you can check the status of each order.

In addition, the online stores will receive a notification to deliver the orders to our warehouse and not to your address. In our warehouse all your orders will first be collected and then delivered all together to you at your preferred time slot and address.

App 2: OnlineSouvenirs

Average customer opinion:



Buy souvenirs online and pick them up at the airport

Name the airport of your departure and your flight number. Based on your flight details, your remaining time for souvenir shopping is calculated.

Use the online shop in the app to choose from a wide selection of typical souvenirs and to complete your order. You can use the online shop already while traveling or during your time at the airport as long as you complete your order within the remaining time for shopping.

The items purchased online will be perfectly packed for the flight and delivered to a pick-up point at the airport. The most convenient location and time will be automatically determined based on the gate and flight time. Check the map to find the pick-up point.

App 3: Train&Adapt

Average customer opinion:

Adjust the exercises during the workouts

Follow the video instructions for your workout. During the 15-second break between exercises, you can decide whether you want to continue with or without equipment and whether you prefer a different intensity or exercise duration so that the next exercises will be adjusted.

If you don't want to adjust anything, just take a 15-second rest and follow the upcoming workout instructions.

Rate the exercises during or after the workout. The exercises in the current workout and of upcoming workouts will be adjusted according to your likes and dislikes.

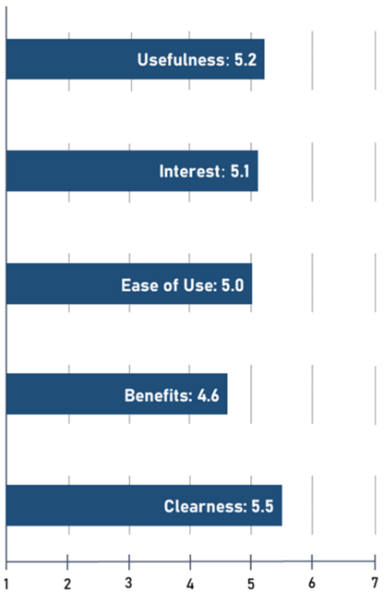
End of Report →

Period 5: market-first | separation low

Market Data and App Descriptions

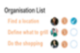
App 1: OrgaReunions

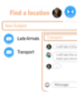
Average customer opinion:



Organize everything for a reunion with your friends

Add a reunion profile.

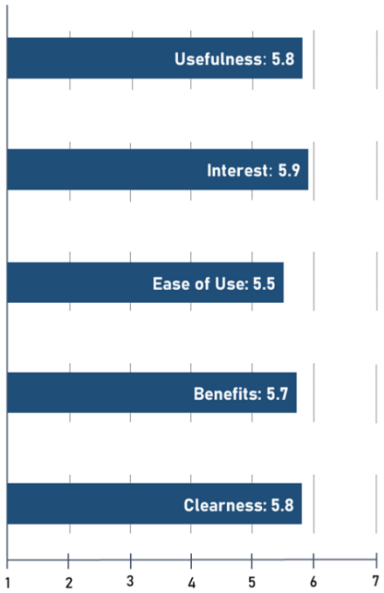

Create a list of things to organize with your friends. Everyone invited can add tasks and mark themselves as the responsible person. With the checkpoints, everyone keeps track of what is already organized and what is not.


If you need to communicate with your friends, you can either chat directly with a responsible person by clicking the chat icon next to the task, or you can start chats with everyone by setting up a chat for a specific subject.

As everything about one topic is communicated in one chat, you can easily keep track of what has already been communicated and agreed upon without endless searching.

App 2: MealSupport

Average customer opinion:



Manage your diet easily with a weekly changing nutrition plan


Select which foods you would like to eat and those you do not eat, and define whether this is for diet reasons or due to food intolerance.

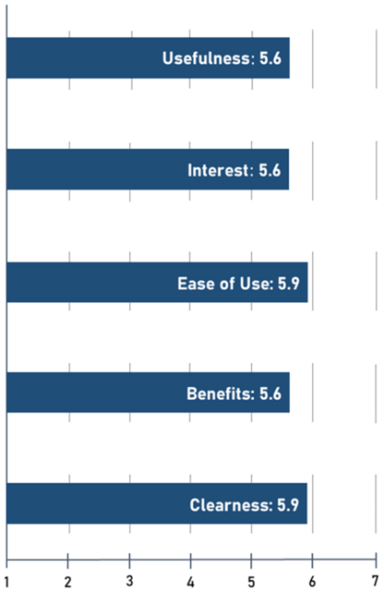
Based on your selection, a meal plan made by dieticians will be recommended.

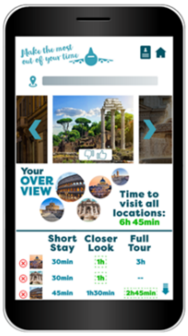

Follow the meal plan and get detailed recipe information and shopping lists each week.


Keep track of the meals you eat each day and your cheat points, i.e. track the meals that were not included in the meal plan. If you go off track and do not follow the meal plan, we will ask you more about the reasons why you did not follow the plan. Based on your answers, the meals will be adjusted, and personalized advice will be given to make it easier for you to continue your diet.

App 3: LocationOverview

Average customer opinion:





Get an overview of locations you want to visit


Search for a city.


Swipe through the images of interesting locations to visit in the chosen city. Like or dislike each location to narrow down your search to locations you want to visit to get an overview of them.


For each location you want to visit, the app displays recommendations for three different durations of stay: (1) the duration needed for a short stay, (2) for a closer look, and (3) for a full tour. Click on one of the three durations for each location to decide how long you would like to stay there.

Based on the chosen duration of stay for each location, the duration to visit all locations will be displayed. If the total duration does not suit you, adjust the durations of the locations.

End of Report →

Order of app presentation per period

Group 1

	DamageReport	SharedExpenses	TrackTrain
Period 1	Mid	Low	High
Usefulness	6.2	5.6	6.4
Interest	5.8	5.7	6.3
Ease of Use	6.5	5.8	6.0
Benefits	5.9	5.5	6.0
Clearness	6.4	5.8	6.1
WTP	2.37	1.97	3.99

	GroupDiscount	PerfectTour	NutriCommunity
Period 2	High	Mid	Low
Usefulness	6.2	6.0	4.9
Interest	6.0	5.9	4.8
Ease of Use	5.8	6.0	5.1
Benefits	6.0	5.9	4.3
Clearness	6.0	6.2	5.5
WTP	3.11	2.44	1.62

	LuggageStorage	RestaurantFinder	OrderOverview
Period 3	Low	High:	Mid:
Usefulness	5.6	6.2	6.0
Interest	5.0	5.7	5.5
Ease of Use	6.0	6.2	6.4
Benefits	4.9	6.4	6.1
Clearness	5.7	5.8	6.4
WTP	1.86	3.59	2.69

	All-in-One	OnlineSouvenirs	TrainAdapt
Period 4	Mid	Low	High
Usefulness	5.2	4.1	5.5
Interest	5.1	4.4	5.4
Ease of Use	6.5	5.3	5.9
Benefits	4.9	3.6	5.5
Clearness	6.5	5.6	6.1
WTP	2.30	1.08	3.70

	OrgaReunions	MealSupport	LocOverview
Period 5	Low	High	Mid
Usefulness	5.2	5.8	5.6
Interest	5.1	5.9	5.6
Ease of Use	5.0	5.5	5.9
Benefits	4.6	5.7	5.6
Clearness	5.5	5.8	5.9
WTP	1.37	3.03	2.67

Group 2

	SharedExpenses	TrackTrain	DamageReport
Period 1	Low	High	Mid
Usefulness	5.6	6.4	6.2
Interest	5.7	6.3	5.8
Ease of Use	5.8	6.0	6.5
Benefits	5.5	6.0	5.9
Clearness	5.8	6.1	6.4
WTP	1.97	3.99	2.37

	PerfectTour	NutriCommunity	GroupDiscount
Period 2	Mid	Low	High
Usefulness	6.0	4.9	6.2
Interest	5.9	4.8	6.0
Ease of Use	6.0	5.1	5.8
Benefits	5.9	4.3	6.0
Clearness	6.2	5.5	6.0
WTP	2.44	1.62	3.11

	RestaurantFinder	OrderOverview	LuggageStorage
Period 3	High	Mid	Low
Usefulness	6.2	6.0	5.6
Interest	5.7	5.5	5.0
Ease of Use	6.2	6.4	6.0
Benefits	6.4	6.1	4.9
Clearness	5.8	6.4	5.7
WTP	3.59	2.69	1.86

	OnlineSouvenirs	TrainAdapt	All-in-One
Period 4	Low	High	Mid
Usefulness	4.1	5.5	5.2
Interest	4.4	5.4	5.1
Ease of Use	5.3	5.9	6.5
Benefits	3.6	5.5	4.9
Clearness	5.6	6.1	6.5
WTP	1.08	3.70	2.30

	MealSupport	LocOverview	OrgaReunions
Period 5	High	Mid	Low
Usefulness	5.8	5.6	5.2
Interest	5.9	5.6	5.1
Ease of Use	5.5	5.9	5.0
Benefits	5.7	5.6	4.6
Clearness	5.8	5.9	5.5
WTP	3.03	2.67	1.37

Group 3

	TrackTrain	DamageReport	SharedExpenses
Period 1	High	Mid	Low
Usefulness	6.4	6.2	5.6
Interest	6.3	5.8	5.7
Ease of Use	6.0	6.5	5.8
Benefits	6.0	5.9	5.5
Clearness	6.1	6.4	5.8
WTP	3.99	2.37	1.97

	NutriCommunity	GroupDiscount	PerfectTour
Period 2	Low	High	Mid
Usefulness	4.9	6.2	6.0
Interest	4.8	6.0	5.9
Ease of Use	5.1	5.8	6.0
Benefits	4.3	6.0	5.9
Clearness	5.5	6.0	6.2
WTP	1.62	3.11	2.44

	OrderOverview	LuggageStorage	RestaurantFinder
Period 3	Mid	Low	High
Usefulness	6.0	5.6	6.2
Interest	5.5	5.0	5.7
Ease of Use	6.4	6.0	6.2
Benefits	6.1	4.9	6.4
Clearness	6.4	5.7	5.8
WTP	2.69	1.86	3.59

	TrainAdapt	All-in-One	OnlineSouvenirs
Period 4	High	Mid	Low
Usefulness	5.5	5.2	4.1
Interest	5.4	5.1	4.4
Ease of Use	5.9	6.5	5.3
Benefits	5.5	4.9	3.6
Clearness	6.1	6.5	5.6
WTP	3.70	2.30	1.08

	LocOverview	OrgaReunions	MealSupport
Period 5	Mid	Low	High
Usefulness	5.6	5.2	5.8
Interest	5.6	5.1	5.9
Ease of Use	5.9	5.0	5.5
Benefits	5.6	4.6	5.7
Clearness	5.9	5.5	5.8
WTP	2.67	1.37	3.03

ESSAY 3

The Effects of Information Restrictions and Justification on Innovation Decisions

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Abstract

To analyze the market potential of new ideas, decision-makers can acquire information on product impressions and/or information on customer problems. The predominant approach in practice involves collecting information on product impressions, providing insights into customers' opinions on the functional aspects of new ideas. However, existing literature suggests that focusing on customer problems would be more beneficial. I first predict and show that decision-makers generally prefer information on product impressions over customer problems. Second, I analyze how decision performance is affected by restrictions on information acquisition and by justification mechanisms. My results show that decision-makers tend to acquire both types of information more frequently in the absence of acquisition restrictions. However, the preference for product impressions leads to greater attention to this information. Due to this selective attention, more information does not result in better decision performance as decision-makers ignore customer problems more likely even though both types of information are acquired. However, the results also reveal that justification increases the likelihood of acquiring and processing both types of information. Thus, justification can have a positive impact on decision performance by reducing selective attention when both types of information are acquired.

Keywords: information acquisition, acquisition restrictions, justification, budget allocation, information on product impressions, information on customer problems

I. Introduction

Innovation resources are usually limited, requiring managers to allocate these carefully to new ideas (Berg 2016; Dziallas 2020; Sukhov et al. 2021; Toubia and Florès 2007). To increase the effectiveness of budget allocation, managers evaluate new ideas by considering market information to analyze their potential (Adams, Day, and Dougherty 1998; Ottum and Moore 1997; Parry and Song 2010; Schmidt, Sarangee, and Montoya 2009). Therefore, managers can acquire information on product impressions and/or customer problems. Information on product impressions informs managers about customer opinions related to functional aspects of new ideas, such as design, functionality, and ease of use (Arts, Frambach, and Bijmolt 2011; Candi et al. 2017; Claudy, Garcia, and O'Driscoll 2015; Homburg, Schwemmle, and Kuehnl 2015). Information on customer problems informs managers about whether customers face a problem and how well new ideas solve the problem (Christensen et al. 2016a; 2016b; Ulwick 2005).

Prior literature states that it is more beneficial for firms to acquire information on customer problems rather than product impressions (Christensen et al. 2016a; 2016b; Ulwick 2005). The reason is that customers often buy products to solve a specific problem. Therefore, firms can enhance market success by providing tailored solutions to address these problems. To decide whether a new idea matches a particular problem, prior literature argues that managers should gain information on customer problems instead of product impressions (Christensen et al. 2016a; 2016b). However, information on product impressions is more commonly used in practice (Moessner et al. 2024; Ulwick 2005; Ulwick and Bettencourt 2008; Wallace 2018).

In a setting where market information can be contradicting, for instance, when new ideas score high on product impressions but low on customer problems, acquiring and processing more likely product impressions can lead to a misinterpretation of the market potential (Christensen et al. 2016a; 2016b; Ulwick 2005; Ulwick and Bettencourt 2008). A new idea high in product impressions but low in customer problems means that customers like the functional aspects but that the new idea does not solve customers' problem effectively. Thus, if managers focus more on product impressions, they may overestimate the potential of ideas scoring high in product impressions but low in customer problems as they fail to acquire or process information on customer problems.[24] To address this management problem effectively, it is essential to understand how control mechanisms used in innovation affect the preference for acquiring and processing information on product impressions over customer problems and, consequently, decision performance. In this study, I investigate the effects of acquisition restrictions and justification on decision performance when allocating budget to new ideas.

To support information acquisition in innovation, firms can aim for a more unrestricted information acquisition process, i.e., allowing managers to choose how much information they want to acquire (Cui and Xiao 2019; Gielnik et al. 2014). Prior literature shows that when managers have the opportunity to acquire more information, they do so, especially in uncertain settings such as innovation (Bastardi and Shafir 1998; Bedford and Onsi 1966; Blandin and Brown 1977). According to economic theory, acquiring more information should generally lead at least to the same or even better decision performance than having a single piece of information. More information can help managers form a clearer picture of the market potential (Simon 1987; Stigler 1961). However, this theory assumes that managers process all available information. Prior psychology research provides evidence that managers' selective attention causes them to focus on specific information rather than processing all acquired information. As a result, managers may not benefit from acquiring more information (Boiney, Kennedy, and

[24] An analysis of the market information collected for this dissertation provides further evidence of the contradicting information setting. I compare the mean values of product impressions indicators versus customer problems indicators for each developed app. I refer to the mean value of those indicators which show a positive significant effect on customers' purchase intention in my first essay. The t-tests show that 10 out of 25 apps score significantly higher on product impressions compared to customer problems. This means that customers like those apps more for their functional aspects than because these apps solve a problem they have. In addition, the descriptive statistics show that some apps score higher on customer problems compared to product impressions, but these differences are not significant. This provides some evidence that in case decision-makers acquire and process only information on product impressions, they might misinterpret the market potential of new ideas. My first essay in this dissertation shows that the customer problems model ($R^2 = 81.07\%$) and the product impressions model ($R^2 = 78.71\%$) predict customers' purchase intention similar well. Nevertheless, the mean values of the indicators, which are provided to decision-makers in practice, can be contradicting, leading to the management problem addressed in this essay. Due to the presence of contradicting information, it is important to understand the information acquisition and processing behavior of decision-makers in terms of the two types of market information.

Nye 1997; Russo, Meloy, and Wilks 2000; Sweeny et al. 2010). Overall, the effect of restrictions on decision performance remains unclear, and the same is true for justification, i.e., when managers need to provide reasons behind their decisions to superiors. While some research shows that justification increases decision performance by improving information processing of all acquired information (Gibbins and Newton 1994; Huber and Seiser 2001; Tetlock, Skitka, and Boettger 1989), other research points out that justification can intensify selective attention (Curley, Yates, and Abrams 1986; Taylor 1995). Since both mechanisms influence information acquisition and processing, they can intensify or weaken each other's effect.

I analyze the effects in a setting where the interpretation of market information is contradicting, i.e., new ideas score higher on product impressions but lower on customer problems or vice versa. To account for this, participants in my experiment need to allocate budget among two ideas: one scores higher in product impressions but lower in customer problems, the other scores higher in customer problems but lower in product impressions. Consequently, the more the participants pay attention to product impressions (customer problems), the more budget is allocated to the idea that scores higher on product impressions (customer problems).

I first predict that decision-makers generally prefer information on product impressions over customer problems. When allocating budget, decision-makers tend to base this decision not only on the status of the innovation but also on the perceived potential for improvement. This is because new ideas need further development to achieve sufficient market potential (Berg 2016; Martinsuo and Poskela 2011). As the development takes place after budgeting, the outcome of the developments is uncertain when allocating budget. To reduce uncertainty, decision-makers prefer information that increases their sense of control (Blandin and Brown 1977; Sweeny et al. 2010). In contrast to information on customer problems, decision-makers consider product impressions as easier information from which they can directly derive whether and how the new idea should be improved (Adams, Day, and Dougherty 1998; Arts, Frambach, and

Bijmolt 2011). This increases their sense of control over further developments and reduces the perceived uncertainty in innovation budgeting (Du et al. 2007; Sweeny et al. 2010).

I then predict that justification intensifies the likelihood that decision-makers prefer product impressions over customer problems and that more information is acquired. Decision-makers aim to acquire information that will allow them to justify their decisions easily. In the presence of restrictions, justification increases their preference for product impressions as it strengthens their confidence that they can justify their decision by the easier derived conclusions (Golman et al. 2022; White, Varadarajan, and Dacin 2003). In the absence of restrictions, they prefer to acquire more information to ensure that they find sufficient reasonable arguments to justify their decision (Ashton 1992; Fennema and Perkins 2008; Tetlock and Boettger 1989).

Regarding the effects on decision performance, I define a baseline hypothesis when decision-makers do not justify their decisions. In this case, decision-makers acquire more likely both types of information in the absence of restrictions to reduce uncertainty (Bastardi and Shafir 1998; Bedford and Onsi 1966). However, due to contradicting information, decision-makers likely process the information selectively by processing the preferred information on product impressions and ignoring more likely information on customer problems (Du et al. 2007; Shah, Friedman, and Kruglanski 2002). Thereby, decision-makers do not anticipate their selective attention bias in the moment of information acquisition. Thus, although decision-makers acquire more information to be better informed, it does not pay off due to their selective attention during information processing (Boiney, Kennedy, and Nye 1997; Russo, Meloy, and Wilks 2000; Sweeny et al. 2010). The selective attention leads to an overestimation of the new idea scoring high in product impressions but low in customer problems, which reduces decision performance when acquisition restrictions are absent compared to present.

Additionally, I investigate the effects of justification on decision performance. As I cannot derive an unambiguous directional prediction based on prior research, I specify a research question. One line states that justification increases selective information attention (Curley, Yates, and Abrams 1986; Taylor 1995) and that more information is acquired (Dalla Via, Perego, and Van Rinsum 2019). This might result in an intensified negative effect of the absence of restrictions on performance. In contrast, other research shows that justification leads to more effort in information processing (Gibbins and Newton 1994; Huber and Seiser 2001; Tetlock, Skitka, and Boettger 1989). This might lead to a positive effect of justification by mitigating selective attention, i.e., increasing the likelihood that both types of information are processed.

I conduct a 2×2 between-participants online experiment on Prolific. Participants take over the role of a product manager in a firm that develops sports apps. Participants are responsible for allocating budget among two new app ideas. Before making these budget allocations, participants receive product information on both apps and then need to acquire market information. First, I manipulate whether acquisition restrictions are present or absent. When restrictions are present, participants can acquire either product impressions *or* customer problems. In contrast, when restrictions are absent, participants can acquire either product impressions *or* customer problems, *or* both. Second, I manipulate whether participants justify their budget allocation. When justification is present, participants are required to allocate budget and write an explanation to justify it. When justification is absent, participants only allocate budget.

The results show a general preference for product impressions over customer problems, consistent with my first hypothesis. Regarding information acquisition, the results show that justification increases significantly the tendency to acquire more information but not the preference for product impressions. In line with my prediction, decision performance decreases in the absence than in the presence of acquisition restrictions when decision-maker do not justify their decision. The results indicate that justification increases the likelihood that both types of information are acquired, leading to higher information costs, but it also leads to more effort in information processing, which reduces selective attention on product impressions.

The findings of the study have important implications for research and practice. I contribute to prior research on the effectiveness of managerial accounting mechanisms in innovation (Bedford 2015; Bisbe and Otley 2004; Davila, Foster, and Oyon 2009). My study contributes to the existing knowledge base by showing that the opportunity to acquire more information is detrimental to decision performance when allocating innovation budget. I show that the absence of acquisition restrictions has a negative effect on decision performance as decision-makers acquire more information but process it selectively. My results also reveal that justification can reduce this selective attention by increasing effort in information processing.

This study provides also insights into decision-makers' information behavior. To the best of my knowledge, this is the first study to provide controlled evidence that decision-makers generally prefer information on product impressions over customer problems. This is because they want to derive direct conclusions on improvement opportunities to control uncertainties in innovation budgeting. To test for an information preference, I design an experiment where participants choose between two types of information that provide different insights but are cost-wise equal. This allows me to test whether a general preference for information on product impressions exists and how this preference influences decision performance under management controls such as acquisition restrictions and justification. I also contribute to research by using real market information in the experiment based on a customer feedback study. Therewith, I provide a method that can increase realism and external validity in an experimental setting.

This study has implications for practice. As the preference for product impressions influences decision-makers' information behavior, firms need to be aware of this when designing mechanisms to facilitate budget allocation. I provide evidence that unrestricted acquisition is not beneficial for decision performance. Thus, investing more resources in information acquisition does not pay off due to the selective attention to product impressions when both types of information are acquired. To improve the processing of both types of information, my results reveal that justification can reduce the selective attention to information on product impressions. Thus, if firms want to base their innovation decisions on both types of information, justification mechanisms can have a positive impact on decision performance.

II. Theory and Hypothesis Development

Background

To facilitate budget allocation in innovation, managers acquire market information to analyze the potential of new ideas. Information on product impressions is used to gain insights into customer opinions on functional aspects of the product by encompassing aspects like design, functionality, or ease of use. It informs managers about what customers like and dislike by focusing on customers' impressions of new ideas (Arts, Frambach, and Bijmolt 2011; Candi et al. 2017; Claudy, Garcia, and O'Driscoll 2015; Homburg, Schwemmle, and Kuehnl 2015).

Prior literature argues that firms rely too much on information on product impressions and do not focus enough on customer problems (Christensen et al. 2016a; Ulwick 2005).[25] They state that customers primarily benefit from the purchase if the product solves their problem and less so if the functional aspects are well-developed, but it does not help with any problem. The better the product fits their problem, the more value customers can gain from their purchase, increasing purchase intention. Thus, firms should gain more knowledge of customer problems and how well new ideas solve these problems to allocate resources to those ideas that are best tailored to the problems (Christensen et al. 2016a; 2016b; Ulwick 2005).

Prior literature also argues that while a new idea should match a specific problem to generate sufficient customer value by solving their problems, the functional aspects can still be improved in case of lower scores (Christensen et al. 2016a; 2016b; Ulwick 2005). According to this, an idea scoring high in product impressions but low in customer problems would be of lower potential than an idea scoring high in customer problems but low in product impressions. Consequently, the basis for deciding whether it is worth investing budget in the development

[25] Firms might incorporate information on customer problems and customer needs before the initial idea development phase to identify innovation opportunities. However, when validating and evaluating new ideas, companies tend to use information about product impressions (Ulwick 2005; Wallace 2018). In contrast, the literature states that information on customer problems should be the focus throughout the whole innovation process. Focusing on customer problems should ensure that the main value for the customer, i.e. the development of a tailored solution to their problem, is always the driving force of innovation rather than the functional aspects of the new idea (Christensen et al. 2016a; 2016b; Ulwick 2005; Ulwick and Bettencourt 2008).

of new ideas should be information on customer problems. This means managers should allocate budget for further development to those ideas scoring high in customer problems, i.e., if the problem the idea addresses exists, and the idea solves the problem to a sufficient degree. Factors relating to the functional aspects can be addressed later during the development process after budget allocation (Christensen et al. 2016a; 2016b; Ulwick 2005).

To account for the fact that contradicting information occurs in practice, i.e., new ideas score low on customer problems but high on product impressions, and vice versa, I examine the effects in a setting where decision-makers have to allocate budget to two new ideas. One new idea scores higher on customer problems but lower on product impressions, while the other new idea scores higher on product impressions but lower on customer problems.

Preference for acquiring product impressions

Due to limited resources for implementing innovation projects, decision-makers allocate budget early in the process by deciding which new ideas are worth investing resources in their further development (Berg 2016; Cooper 2013; Dziallas 2020; Sukhov et al. 2021). However, the future potential of new ideas is uncertain, especially in the early stages of innovation. Even though the ideas that receive budget are considered promising, firms often have to improve them based on customer feedback to achieve sufficient market success (Berg 2016; Martinsuo and Poskela 2011). When allocating budgets, the outcome of further developments is still uncertain to decision-makers. Consequently, it is uncertain whether the decision to invest resources in the development of promising ideas will pay off in the end (Carson, Wu, and Moore 2012; MacCormack and Verganti 2003; Marsh and Stock 2006; West, Acar, and Caruana 2020).

According to prior research, decision-makers believe having some control over the situation reduces the likelihood that uncertain outcomes will turn negative (Du et al. 2007; Keh, Foo, and Lim 2002; Leotti, Iyengar, and Ochsner 2010). Therefore, it is important for decision-makers to have a sense of control over issues with the new idea to cope with the uncertainties of further development. Since decision-makers prefer information that increases their sense of control when allocating budget (Blandin and Brown 1977; Mueller et al. 2018; Sweeny et al. 2010), I expect decision-makers to prioritize information on product impressions. I suggest that decision-makers perceive that this information makes it easier for them to draw conclusions on improvement opportunities. The reason is that they can derive insights directly from the information on whether the firm needs to improve functional aspects such as design, functionality, or user-friendliness. This helps them to determine whether and how the firm is able to improve the new idea based on customer feedback to increase its future potential (Adams, Day, and Dougherty 1998; Arts, Frambach, and Bijmolt 2011; Claudy, Garcia, and O'Driscoll 2015; Sharot and Sunstein 2020). By focusing on product impressions, decision-makers gain more likely a greater sense of control over development issues, which in turn reduces their perceptions of future uncertainties (Du et al. 2007; Sweeny et al. 2010).

In general, both types of information, product impressions and customer problems, can inform about improvement potentials. However, acquisition preferences are influenced by decision-makers' perception of the ease of deriving conclusions. The easier it is to derive conclusions from the information, the greater the perceived information utility by increasing perceived control and the more the information is preferred (Foust and Taber 2023; Golman et al. 2022; Sharot and Sunstein 2020; Sweeny et al. 2010). Regarding customer problems, decision-makers likely perceive the information as less easy to derive direct conclusions for improvements. The conclusions drawn from customer problems are more of a relational nature. With customer problems, decision-makers need to find out the problems of customers and how a new idea is solving the problems, resulting in more relational thinking regarding the problem and solution fit (Christensen et al. 2016a; 2016b). Consequently, I expect that, in general, decision-makers prefer information on product impressions over customer problems.

H1: Generally, decision-makers acquire more likely information on product impressions over customer problems.

Effects of acquisition restrictions and justification on information acquisition

In the presence of acquisition restrictions, I expect that justification increases the likelihood of acquiring information on product impressions over customer problems. Justification can heighten decision-makers' desire to control the situation. Therefore, justification can increase the preference for information that reinforces decision-makers' sense of control such as information on product impressions (Adams, Day, and Dougherty 1998; Curley, Yates, and Abrams 1986; Du et al. 2007; Sweeny et al. 2010; Taylor 1995). With product impressions, decision-makers can perceive it as easier to justify their decision. Product impressions provide them more straightforward with arguments as to why a new idea is already good and how it can be improved to become even better in the future. This strengthens their confidence that they can justify their budget decision (Golman et al. 2022; White, Varadarajan, and Dacin 2003; Wilton and Myers 1986). Thus, in the presence of acquisition restrictions, I expect that justification strengthens the general preference for product impressions and, hence, its acquisition.

H2a: In the presence of acquisition restrictions, the likelihood that information on product impressions is acquired is higher under justification present than absent.

In the absence of acquisition restrictions, decision-makers, in general, tend to acquire more information, particularly in uncertain settings such as budget allocation in innovation. The reason is that more information should reduce uncertainty. Decision-makers feel better informed when they acquire more information (Bastardi and Shafir 1998; Bedford and Onsi 1966; Blandin and Brown 1977). This sense of being better informed enhances their perception of control in uncertain situations and strengthens their confidence in making decisions (Dummel, Rummel, and Voss 2016; White, Varadarajan, and Dacin 2003). Therefore, if decision-makers can acquire more information, they are less likely to limit their information acquisition and more likely to acquire more information. Applied to my setting, decision-makers consequently acquire more likely both types of information, i.e., product impressions and customer problems, in the absence of acquisition restrictions.

When justification is required, decision-makers tend to increase their information acquisition even more to strengthen their argumentation. Under justification, decision-makers know that the reasoning for their decision will be evaluated (Johnson and Kaplan 1991; Lerner and Tetlock 1999). As a result, they increase their information acquisition to ensure they can provide sufficiently reasonable arguments. They perceive that more information helps them to better support their decision (Ashton 1992; Dalla Via, Perego, and Van Rinsum 2019; Fennema and Perkins 2008; Tetlock and Boettger 1989). As a result, acquiring more information strengthens not only their confidence in their decision but also their ability to justify it (Dummel, Rummel, and Voss 2016; White, Varadarajan, and Dacin 2003). If they are required to justify their decision, the need for more information becomes more apparent. Thus, justification intensifies the tendency to acquire more information in the absence of acquisition restrictions.

H2b: In the absence of acquisition restrictions, the likelihood that both types of information are acquired is higher under justification present than absent.

Effects of acquisition restrictions and justification on decision performance

To determine the effects on decision performance, I first define a baseline hypothesis related to the effects of acquisition restrictions when decision-makers are not required to justify their decision. As described above, decision-makers generally tend to acquire more information in the absence of acquisition restrictions. Particularly in uncertain settings such as innovation, decision-makers increase their information acquisition to feel better informed. This leads to a greater sense of control to cope with uncertainties and, in turn, improves decision confidence (Bastardi and Shafir 1998; Bedford and Onsi 1966; White, Varadarajan, and Dacin 2003).

As information acquisition is costly, acquiring more information results in higher costs. The higher acquisition cost can only be reasonable if more information increases the decision outcome substantially compared to when less information is acquired (Bedford and Onsi 1966; Blankespoor et al. 2019). From a purely economic perspective, having more information should lead at least to the same or even better decision performance than having only one piece of information. More information should help to provide a more complete picture and a better understanding of the situation in question (Simon 1987; Stigler 1961).

However, in case of contradicting information, decision-makers will likely process information selectively rather than weighing it objectively (Du et al. 2007; Shah, Friedman, and Kruglanski 2002). If information on product impressions and customer problems point in different directions, decision-makers are likely to focus their attention on product impressions, as it increases more likely their sense of control to better deal with uncertainties (Adams, Day, and Dougherty 1998; Du et al. 2007; Sweeny et al. 2010). Thus, information on customer problems is more likely ignored even though both types of information are acquired (Foust and Taber 2023; Golman et al. 2022; Shah, Friedman, and Kruglanski 2002).

Decision-makers do not anticipate their selective attention bias in the moment of information acquisition. Thus, decision-makers acquire more information to feel better informed and increase their decision confidence (Bastardi and Shafir 1998; Bedford and Onsi 1966; White, Varadarajan, and Dacin 2003). However, due to the selective attention when processing the information, acquiring more information does not pay off (Boiney, Kennedy, and Nye 1997; Russo, Meloy, and Wilks 2000; Sweeny et al. 2010). The selective attention in terms of processing more likely information on product impressions and ignoring more likely information on customer problems biases them towards allocating more budget to the idea high in product impressions but low in customer problems. Consequently, decision-makers cannot translate more information into better decision outcomes to account for the higher acquisition cost. As more decision-makers acquire both types of information in the absence of restrictions, I predict that decision performance is lower when acquisition restrictions are absent than present.

H3: Decision performance is lower in the absence of acquisition restrictions compared to the presence of acquisition restrictions when justification is absent.

The previously defined effects of justification on information acquisition and processing can indicate an intensified negative effect on decision performance for at least two reasons. First, justification can intensify the likelihood that more information is acquired (Ashton 1992; Fennema and Perkins 2008; Tetlock and Boettger 1989). Second, justification can increase the preference for information that increases the sense of control, such as information on product impressions (Curley, Yates, and Abrams 1986; Taylor 1995). Thus, justification can have a negative effect by increasing the likelihood of acquiring both types of information and increasing selective attention when processing the information. Justification would intensify the negative effect of the absence of restrictions on decision performance.

However, other research shows that justification can also lead to more effort in information processing due to a motivational effect of justification (Lerner and Tetlock 1999; Tetlock, Skitka, and Boettger 1989). Under justification, the benefits of a better judgment exceed the cost of processing, resulting in greater information processing effort. Thus, decision-makers are more likely to process all available information to derive more reasonable arguments, as they do not want to miss any relevant information (Gibbins and Newton 1994; Huber and Seiser 2001). This motivational effect could cancel out the negative effects from acquiring more information as justification would reduce the selective attention, i.e., it mitigates the preference for processing more likely product impressions. This implies that when decision-makers acquire both types of information, the budget allocation will be based more on both types of information, resulting in a positive effect of justification. Thus, it can also be assumed that justification mitigates the negative effect of the absence of restrictions on decision performance by increasing effort in information processing. As the described effects of justification based on prior research go in opposite directions, I specify a research question to examine the effects of justification on decision performance.

RQ: How does justification influence the effect of acquisition restrictions on decision performance in innovation budget allocation?

III. Method

Experimental design and task

To test the hypotheses, I conduct a 2 × 2 between-subjects experiment. Two factors are manipulated: (1) acquisition restrictions (*absent vs. present*) and (2) justification (*absent vs. present*)[26]. The experiment spans two periods. Having two periods allows me to test the influence of acquisition restrictions and justification on information acquisition and decision performance in a one-shot setting, as well as the effects on information acquisition after participants receive information on their performance in period 1. For the study, participants assume the role of a product manager in a firm that develops sports apps. They are responsible for allocating the budget among two new ideas in each period. Before making these budget allocations, participants first receive product information on both apps and then need to acquire market information, i.e., product impressions and/or customer problems.

Experimental manipulations

First, I manipulate whether acquisition restrictions are absent or present. When restrictions are present, participants acquire a single piece of information, i.e., either information on product impressions *or* customer problems. When restrictions are absent, participants can acquire a single piece of information or both pieces of information, i.e., information on product impressions *or* customer problems, *or* both types of information.[27]

Second, I manipulate whether participants are required to justify their budget allocation. Under justification present, participants are required to write an explanation to justify their decision. Participants are informed that they have to outline the reasoning behind their budget allocation by presenting arguments that justify their decision. In addition, participants were

[26] The experiment was approved by the ethics committee of the university the author is affiliated with.
[27] In the instructions participants get informed about each type of information by a general definition and a description of each indicator as presented in the Appendix.

informed that the justification will be evaluated. This manipulation is derived from prior research (see: Dalla Via, Perego, and Van Rinsum 2019; DeZoort, Harrison, and Taylor 2006; Libby, Salterio, and Webb 2004) and takes the definition by Lerner and Tetlock (1999) into account. According to Lerner and Tetlock (1999), justification is defined by the participants' expectation that they have to give reasons and that this explanation will be evaluated.[28] Under justification absent, participants are informed that they only allocate the budget, do not have to explain the reasons behind their budget allocation and that their reasons will not be evaluated.

Product and market information

For the product information, I design presentations for four sports apps (two rounds of two apps). These presentations include a picture of the app and a description of its features. The market information used in the experiment is derived from a self-designed survey on customer feedback previously conducted on Amazon Mechanical Turk (see: essay 1). Participants evaluate the sports apps based on the designed presentations across product impressions indicators or customer problems indicators. In addition, they express their willingness to pay (WTP) for each app. The WTP represents the maximum subscription fee that customers are willing to pay in dollars per month for an app. It indicates the market potential of the apps (Breidert, Hahsler, and Reutterer 2006; Wertenbroch and Skiera 2002). To generate the information, I use in the experiment, I refer to a subsample that is more likely to represent a realistic target group to reduce noise. The target group sample consists of participants who are highly involved in the respective domain, very open to innovation, and generally willing to pay for an app.

Depending on their information acquisition, participants in the experiment receive the mean values of five indicators on product impressions and/or customer problems based on the

[28] To test whether participants are committed to justification, I ask two post-experimental questions, measured on a 7-point Likert scale from strongly disagree to strongly agree: (1) It was very important for me to write a convincing justification for my budget allocation, (2) I was highly motivated to provide a justification that would convince my superior. The measures show mean values of 5.47 and 5.42 and median values of 6, indicating high commitment to justification.

target group ratings. Information on product impressions informs participants about customers' impressions of the functional aspects of the apps. It indicates whether they liked the design and features and how easy they find it to use. Information on customer problems informs participants about whether customers face a specific problem that the apps solve, how strongly their sports experience is affected by this problem, and to what extent the apps solve the problem.

I analyze the effects of acquisition restrictions and justification in a setting where the market information is contradicting. This means that a new idea scores higher (lower) in product impressions but lower (higher) in customer problems. Thus, in my experiment, one app scores higher on three out of five indicators for product impressions, while the other app scores higher on three out of five indicators for customer problems.[29] Consequently, participants who pay more attention to product impressions (customer problems) will likely allocate more budget toward the app higher in product impressions (customer problems). The product and market information provided to participants in period 1 are presented in the Appendix.

Budget allocation, information acquisition, and bonus

For the budget allocation, participants receive a budget of 100 units in every period. Participants are required to invest the 100 units entirely in the apps by dividing the 100 units

[29] To keep experimental control, some mean values of the indicators were slightly adjusted to achieve more consistency and substantial differences between the indicators across apps. The difference in mean values per indicator is always at least 0.2 between the two apps. The app scoring higher on customer problems shows higher mean values on the indicators Degree of Problem, Level of Difficulty, and Improvement. In line with this relational direction Degree of Problem and Improvement show significant positive effects on desirability and consequently on WTP in the customer feedback study (essay 1). Level of Difficulty is insignificant. However, I opted for Level of Difficulty because it strengthens the participants' conceptual understanding of the customer problems concept, as it is also related to the customer problem itself. In addition, consistent with my analyzed setting, the app scoring higher in customer problems has a higher WTP. This means that the three product impressions indicators the other app scores higher on should have no effect or a negative effect on WTP, i.e., even if customers rate the other app higher on these indicators, they are less likely to buy it. While Excitement and Clearness are in line with this, Design shows a significant positive effect in my first essay. However, I opted for Design as this indicator also strengthens the understanding of the concept by relating highly to the functional aspects of the apps. For more experimental control it is important to strengthen the understanding of the underlying principles of the two types of information to ensure that participants can more easily distinguish them from each other. For more information on the indicators and their effect on customers' purchase intention, please refer to the first essay in this dissertation.

among them. To measure the effectiveness of the budget allocation, I calculate a total return by multiplying the budget units for each app by its WTP[30]. The total return is computed as follows:

total return = units allocated to app1 x WTP app1 + units allocated to app2 x WTP app2

Consequently, the more budget is allocated to the app with the higher WTP, the greater the total return. Consistent with my analyzed setting, the app higher in customer problems has a higher WTP compared to the app higher in product impressions. The total return ranges from 396 to 453 points in period 1 and from 419 and 468 points in period 2. After the deduction of the fixed project cost of 390 units, the total return corresponds to the participant bonus. The project cost is constant in the experiment across conditions and periods and never exceeds the total return. Thus, the bonus can never be negative. As the bonus depends on the total return, the bonus increases when more budget is allocated to the app with higher WTP. Every 10 units allocated to the app with the higher WTP results in an increase of 5 units in bonus. 5 units of bonus are converted to £0.025 of variable compensation for participants.

For the information acquisition participants receive an additional budget of 10 units in both periods. One piece of information costs 5 units. In the experiment, participants are required to acquire at least one piece of information. Thus, at least 5 units need to be spent in all conditions for information acquisition. All participants are informed that the remaining units, which are not invested in information acquisition, will be added to their bonus. In the restriction present conditions, this means that participants automatically receive 5 units of additional bonus. In the restriction absent conditions, participants decide to use the entire 10 units to acquire both types of information or invest only 5 units to acquire one type of information. Thus, participants in the restriction absent condition need to trade off spending more for the information acquisition and receiving both types of information or acquiring one type of information and receiving 5 units of an additional bonus. As described above, 10 units allocated to the higher WTP app

[30] The WTP of each app is based on the mean values of the target group sample from the first essay. Period 1: \$4.53 and \$3.96: Period 2: \$4.68 and \$4.19. The difference between the WTP in both periods is around \$0.50.

result in 5 more units in bonus. Thus, the decision to acquire both types of information by investing 5 units more would pay off if the participants shifted at least 10 budget units to the app with the higher WTP. The final bonus points depend on the total return and information acquisition. The bonus is computed as follows:

bonus = total return – fixed project costs + remaining acquisition units

Dependent variable

The dependent variable *decision performance* is measured by the bonus the participants achieve in period 1.[31] It captures their performance in terms of the decision outcome, i.e., the effectiveness of budget allocation, and accounts for information acquisition costs. With this, I account for costly information acquisition and that more information acquisition needs to be compensated by a higher decision outcome than when a single piece of information is acquired.

Procedures and participants

For the experiment, participants were recruited from the web-based crowdsourcing platform Prolific. Participation was restricted to participants living in the U.S., who are fluent in English and working primarily in the following sectors: business management and administration or marketing and sales. The participants were asked these pre-screening questions again at the beginning of the experiment. Only those who were consistent in their responses to the questions and the information they provided in their Prolific profile were allowed to participate in the experiment.[32]

[31] The focus of this study is the influence of acquisition restriction and justification on information acquisition and decision performance. Thus, the main analysis focuses on the effects in period 1. I use the data of period 2 for a supplemental analysis on the effects of feedback. Performance over time can be affected when the same type of information is acquired compared to when a different type of information is acquired in different periods. By focusing on the first period, I can test the theory in a most unpolluted setting possible by excluding effects of previous decision performance and previously acquired information.

[32] To ensure high quality participation the pool was also restricted to participants who have an approval rate of 98% or higher and who already had a minimum of 50 submissions on Prolific. Participants are required to pass two attention checks and could only process to period 1 of the experiment when answered both questions correctly (Bentley 2021; Peer et al. 2022).

The participants are randomly assigned to the four experimental conditions. In the instructions, participants receive information about the two types of information they can acquire. Participants get informed about them by a general definition and by receiving a description of each indicator. The definitions and descriptions participants receive are those presented in the Appendix. After taking a quiz to ensure understanding of the instructions, participants are given the product information of the first two apps. After familiarizing themselves with the product information for at least 30 seconds, participants acquire the market information. Participants assess the acquired market information for at least 30 seconds before proceeding to the budget allocation task. After allocating the budget to the two apps, participants are required to write a justification statement in the justification present conditions. At the end of the period, participants receive feedback on the WTP for each app, the budget return, and their bonus points before proceeding to period 2. The procedure of period 2 is equal to the procedure of period 1, but with two different sports apps than in period 1.

A total of 299 participants completed the experiment on Prolific. For the final sample, 15 participants were excluded due to duplicate IP to prevent ballot stuffing or the use of mobile devices, as the experimental information can only be adequately displayed on computer or laptop screens. In addition, 53 participants who failed at least one of two manipulation checks were excluded.[33] The first manipulation check assesses their attentiveness to acquisition restrictions, and the second to justification. The first question asks participants whether they have the option to acquire more than one type of customer feedback. The second question asks about whether they have to justify their budget allocation. The final sample consists of 231 participants.

Participants completing the experiment received a fixed pay of £2.80 and variable pay depending on their decision performance in every period. On average, participants received a

[33] The frequency of eliminating participants is neither affected by acquisition restrictions ($\chi 2 = 3.14$, $p = 0.370$) nor by justification ($\chi 2 = 0.81$, $p = 0.848$). All statistical inferences of hypothesis tests remain the same when including them.

variable pay of £0.48 and completed the experiment in 23 minutes. The final compensation (sum of fixed pay and variable pay) represents, on average, a good hourly payment rate on Prolific.[34] Participants of the final sample are, on average, 39 years old and have, on average, six years of experience in marketing, around three and a half years of experience in research and development, and three years of product manager experience.

IV. Results

Descriptive Statistics

Table 1 reports the descriptive statistics for information acquisition in period 1. It presents the percentage of participants per condition and the type of information acquired. The descriptive statistics show that, in general, participants prefer more likely product impressions over customer problems (total sample: 43.72% vs. 32.47%; subsample in case one type of information is acquired: 57.39% vs. 42.61%). This shows initial evidence in line with H1. The descriptive statistics also show that 46.22% of participants acquire both types of information when acquisition restrictions are absent. The likelihood that both types of information are acquired is higher under justification present than absent (56.90% vs. 36.07%) in line with H2b.

Table 2 reports the descriptive statistics for the dependent variable *Decision Performance* across experimental conditions and the type of information acquired. It shows the mean values and standard deviations. The descriptive statistics show that the decision performance is lower in the absence than presence of restrictions (36.01 vs. 39.18) when justification is absent. This represents initial evidence in line with H3. It also reveals that the decision performance is quite similar under justification present and absent in the absence (36.14 vs. 36.01) and presence of restrictions (38.96 vs. 39.18).

[34] Prolific requires a minimum hourly rate of £6.00 and recommends £9.00 (Prolific 2024). The hourly rate in my experiment varies between £7.85 and £9.28, depending on the variable pay between £0.21 and £0.76.

TABLE 1
Information Acquisition

Descriptive statistics – Percentage of participants per type of feedback acquired

		product impression	*customer problems*	*both*	*Total*
Restriction absent	*Justification absent*	29.51% n=18	34.43% n=21	36.07% n=22	100.00% n=61
	Justification present	27.59% n=16	15.52% n=9	56.90% n=33	100.00% n=58
	Total	28.57% n=34	25.21% n=30	46.22% n=55	100.00% n=119
Restriction present	*Justification absent*	57.63% n=34	42.37% n=25	---	100.00% n=59
	Justification present	62.26% n=33	37.74% n=20	---	100.00% n=53
	Total	59.82% n=67	40.18% n=45	---	100.00% n=112
Total		43.72% n=101	32.47% n=75	23.81% n=55	100.00% n=231
One type of information acquired		57.39% n=101	42.61% n=75	---	100.00% n=176

Table 1 presents the descriptive statistics of period 1 regarding the percentage of participants per condition and type of information acquired.

TABLE 2
Decision Performance

Descriptive statistics – Mean (standard deviation)

		product impression	*customer problems*	*both*	*Total*
Restriction absent	*Justification absent*	35.23 (9.84) n=18	41.13 (13.89) n=21	31.78 (8.82) n=22	36.01 (11.61) n=61
	Justification present	35.15 (12.08) n=16	40.45 (11.75) n=9	35.45 (9.00) n=33	36.14 (10.33) n=58
	Total	35.19 (10.78) n=34	40.93 (13.09) n=30	33.98 (9.03) n=55	36.08 (10.96) n=119
Restriction present	*Justification absent*	36.16 (11.35) n=34	43.28 (12.82) n=25	---	39.18 (12.40) n=59
	Justification present	37.77 (15.31) n=33	40.93 (14.95) n=20	---	38.96 (15.11) n=53
	Total	36.96 (13.37) n=67	42.24 (13.69) n=45	---	39.08 (13.69) n=112
Total		36.36 (12.53) n = 101	41.71 (13.38) n=75	33.98 (9.03) n=55	37.53 (12.42) n=231

Table 2 presents the descriptive statistics regarding the mean values of the dependent variable *Decision Performance* per type of information acquired and condition. *Decision performance* is measured by the bonus points participants reach in period 1. The bonus is computed as follows: bonus = total return – fixed project costs + remaining acquisition units. It ranges from 6 to 63 points.

Hypotheses Test

Preference for acquiring product impressions

I first predict that decision-makers generally prefer and consequently acquire more likely product impressions over customer problems. I run a binominal test to test whether the frequency of acquiring product impressions differs significantly from 0.5, i.e., is significantly different from an equal, random distribution. The sample consists of participants who acquire a single piece of information in period 1, excluding all participants who acquire both types of information. The two-level categorical dependent variable *AcqOne* equals to 1 if product impressions is acquired and 0 if customer problems is acquired. Table 3 Panel A reports the results of the binominal test. It shows that the proportion of product impressions significantly differs from 0.5 (p = 0.06). In fact, it is significantly higher than 0.5 (p = 0.03), supporting H1.

TABLE 3
Preference for Product Impressions

Panel A: Preference for acquiring product impressions – binominal test

N	Observed k	Expected k	Assumed p	Observed p
176	101	88	0.5	0.57

Pr(k >= 101)	= 0.03 (one-sided test)
Pr(k <= 101)	= 0.98 (one-sided test)
Pr(k <= 75 or k >= 101)	= 0.06 (two-sided test)

Panel B: Test across conditions - ANOVA

	df	MS	F	p
condition	3	.242618395	0.99	0.401

Table 3 Panel A presents the binominal test for H1. The two-level categorical dependent variable *AcqOne* for the binominal test equals to 1 if product impressions is acquired and 0 if customer problems is acquired. I test whether the frequency of product impression acquisition is significantly different from 0.5. I use the subsample of those participants who acquire one type of information in period 1 by excluding all participants acquiring both types of information. Panel B represents a one-way ANOVA to test whether the preference for product impressions differs across conditions. The ANOVA consists of *AcqOne* as the dependent variable and *Condition* as the independent variable. * $p \leq 0.10$; ** $p \leq 0.05$; *** $p \leq 0.01$; p-levels are two-tailed.

A further one-way ANOVA, presented in Table 3 Panel B, with *AcqOne* as the dependent variable and *Condition* as the independent variable reveals that the frequency of acquiring product impressions is not significantly different across conditions ($F = 0.99$, $p = 0.401$). This shows that decision-makers, in general, prefer product impressions over customer problems.

Effects on information acquisition

I predict that in the presence of restrictions, the likelihood that product impressions is acquired is higher under justification present than absent. I test H2a using $\chi 2$-test. The variables are *Justification* (equals to 1 if present and 0 if absent) and *AcqOne* (equals to 1 if product impressions is acquired and 0 if customer problems is acquired). The sample includes participants in the restriction present conditions. The results are reported in Table 4 Panel A. It reveals that even though the frequency of acquiring product impressions increases when justification is present compared to absent, this effect is insignificant (62.26% vs. 57.63%, $p = 0.617$).

Additionally, I predict that in the absence of acquisition restrictions, the likelihood that both types of information are acquired is higher under justification present than absent. I test H2b using $\chi 2$-test. The variables are *Justification* (equals to 1 if present and 0 if absent) and *AcqBoth* (equals to 1 if both types of information are acquired and 0 if one type of information is acquired). The sample includes participants in the restriction absent conditions. The results are presented in Panel B. It shows that justification present significantly increases the likelihood that both types of information are acquired compared to justification absent (56.90% vs. 36.07%, $p = 0.02$), supporting H2b.

TABLE 4
Effects on Information Acquisition

Panel A: Frequency of acquiring product impressions – χ2-test

	Customer Problems	*Product Impressions*	*Total*
Justification absent	42.37% n=25	57.63% n=34	100.00% n=59
Justification present	37.74% n=20	62.26% n=33	100.00% n=53
Total	40.18% n=45	59.82% n=67	100.00% n=112
			χ2 (p): 0.2498 (0.617)

Panel B: Frequency of acquiring both types of information – χ2-test

	One type of information	*Both types of information*	*Total*
Justification absent	63.93% n=39	36.07% n=22	100.00% n=61
Justification present	43.10% n=25	56.90% n=33	100.00% n=58
Total	53.78% n=64	46.22% n=55	100.00% n=119
			χ2 (p): 5.19 (0.02**)

Table 4 Panel A presents the χ2-test testing the effect of justification on the frequency of acquiring product impressions compared to customer problems under restriction present in period 1. The variables are *Justification* (equals to 1 if present and 0 if absent) and *AcqOne* (equals to 1 if product impressions is acquired and 0 if customer problems is acquired). Panel B presents the χ2-test testing the effect of justification on the frequency of acquiring both types of information compared to one type of information under restriction absent in period 1. The variables are *Justification* (equals to 1 if present and 0 if absent) and *AcqBoth* (equals to 1 if both types of information is acquired and 0 if one type of information is acquired). * $p \leq 0.10$; ** $p \leq 0.05$; *** $p \leq 0.01$

Effects on decision performance

To test the effects on decision performance, I regress *Decision Performance* on *Restriction Absent* (equals to 1 if restrictions are absent and 0 if present), *Justification* (equals to 1 if justification is present and 0 if absent), and the interaction of the two variables. The results are presented in Table 5.

TABLE 5
Effects on Decision Performance

Effects of Restriction Absent and Justification on Decision Performance	
Constant	39.18 (1.62) p<0.001
Restriction Absent	-3.17 (2.27) p=0.08*
Justification	-0.22 (2.35) p=0.926
Restriction Absent * Justification	0.35 (3.27) n=0.915
Simple effect of Restriction Absent when Justification is 0 (absent)	-3.17 p=0.08*
Simple effect of Restriction Absent when Justification is 1 (present)	-2.82 p=0.233
Adjusted-R^2	0.002
N	231

Table 5 presents the regression of D*ecision Performance* on *Restriction Absent* (equals to 1 if restrictions are absent and 0 if present), *Justification* (equals to 1 if justification is present and 0 if absent), and the interaction of the two variables. *Decision Performance* is measured by the bonus points participants reach in period 1 for both models. The bonus is computed as follows: bonus = total return – fixed project costs + remaining acquisition units. * $p \leq 0.10$; ** $p \leq 0.05$; *** $p \leq 0.01$; p-levels are one-tailed for directional expectations and two-tailed otherwise.

Consistent with H3, the coefficient of *Restriction Absent,* reflecting the simple effect of restriction absent versus present under justification absent, is significantly negative (β = -3.17, p = 0.08)[35]. Thus, decision performance is negatively influenced by the absence of acquisition restrictions when justification is absent. The regression model also reveals a positive but insignificant interaction term of *Restriction Absent* and *Justification* (β = 0.35, p = 0.915). Additionally, the simple effect of restriction absent versus present under justification present is negative but insignificant (β = -2.82, p = 0.233).

Test of RQ

By testing H2b, I already provide evidence that justification intensifies the effect of acquiring both types of information. As stated in my theory section, justification can either increase the selective attention on product impression or increase effort in information processing, which in turn reduces the selective attention. In case of a reduced selective attention, justification might cancel out the negative effect of acquiring more information in terms of the higher acquisition costs. As the interaction term is insignificant, it can be expected that justification leads to more effort in information processing, as this would lead to a possible countereffect to the higher information costs and consequently to an insignificant effect. To provide further evidence of whether justification increases effort in information processing, I test the effects of justification on budget allocation when both types of information are acquired.

I measure the variable *Budget Allocation* by the units allocated to the app scoring higher in customer problems, i.e. the higher WTP app. Values above 50 indicate that more resources are allocated to the app scoring higher in customer problems, while values below 50 indicate that more resources are allocated to the app higher in product impressions. In case of values above 50, decision-makers bias less likely to the information on product impressions. This

[35] P-levels in this section are one-tailed for directional expectations and two-tailed otherwise.

means that decision-makers more likely process all available information, resulting in a reduced selective attention by more effort in information processing. In contrast, in case of values below 50, decision-makers overestimate the potential of the app scoring higher on product impressions by paying more attention to the information on product impressions (selective attention).

Table 6 Panel A presents descriptive statistics on *Budget Allocation*. Under justification absent, the average budget allocation is below 50 when both types of information are acquired (45.23). In contrast, under justification present, the average budget allocation is above 50 when both types of information are acquired (51.67). This shows initial evidence that in the absence of justification, decision-makers are biased toward the app scoring higher on product impressions when both types of information are acquired, indicating selective attention. In contrast, justification leads to more effort in information processing, which reduces selective attention.

A further regression presented in Panel B Model 1 shows a positive and marginally significant effect of *Justification* on *Budget Allocation* when both types of information are acquired ($\beta = 6.44$, $p = 0.07$ one-tailed). Thus, when both types of information are acquired, more budget is allocated to the app scoring higher on customer problem under justification present compared to absent. This indicates more effort in information processing under justification, as decision-makers are less biased toward the app scoring higher in product impressions.

Due to the limited resources for innovation projects, a new idea with lower budget might be terminated to save resources for future ideas. Thus, it also matters whether decision-makers prefer the higher WTP app, i.e., by allocating more resources to it than the other app (Berg 2016; Cooper, Edgett, and Kleinschmidt 2001; Toubia and Florès 2007). I define the binary variable *ProductPref* that equals to 1 if more than 50 units are allocated to the high WTP app and 0 otherwise. I use a login regression to regress *ProductPref* on *Justification* when both types of information are acquired. The results are presented in Panel B Model 2 and show a positive and marginally significant coefficient of *Justification* on *ProductPref* when both types of information are acquired ($\beta = 0.94$, $p = 0.08$ one-tailed). This provides further evidence that justification increases the preference for the higher WTP app by reducing the bias in favor of the app higher in product impressions, i.e. by reducing selective attention.

TABLE 6
Effects of Justification

Panel A: Effectiveness of budget allocation – Mean (standard deviation)

	product impressions	*customer problems*	*both*	*Total*
Justification absent	42.5 (17.26) n=18	52.86 (24.37) n=21	45.23 (15.47) n=22	47.05 (19.63) n=61
Justification present	42.38 (21.19) n=16	51.67 (20.62) n=9	51.67 (15.79) n=33	49.10 (18.31) n=58
Total	42.44 (18.91) n=34	52.50 (22.96) n=30	49.09 (15.84) n=55	48.05 (18.95) n=119

Panel B: Effects of justification – Regression

	Model 1	Model 2
Constant	45.23 (3.34) p<0.001***	-1.50 (0.55) p=0.007***
Justification	6.44 (4.31) p=0.07*	0.94 (0.66) p=0.08*
R^2	0.02	0.03
N	55	55

Table 6 Panel A presents the descriptive statistics of *Budget Allocation* under restriction absent per type of information acquired. I measure *Budget Allocation* by the units allocated towards the app scoring higher in customer problems in period 1. Values above 50 means that on average more resources are allocated to the app scoring higher in customer problems, while values below 50 means that on average more resources are allocated to the app scoring higher in product impressions. Panel B Model 1 reports the regression of *Budget Allocation* on *Justification* (equals to 1 if justification is present and 0 if absent) when both types of information are acquired. Panel B Model 2 reports the logit regressions of *ProductPref* (equals to 1 if more than 50 units are allocated to the high WTP app and 0 otherwise) on *Justification* (equals to 1 if justification is present and 0 if absent) when both types of information are acquired. * $p \leq 0.10$; ** $p \leq 0.05$; *** $p \leq 0.01$; p-levels are one-tailed.

To summarize, justification intensifies the likelihood that both types of information are acquired in the absence of acquisition restrictions leading to higher acquisition cost compared to when one type of information is acquired. Nevertheless, justification also leads to more effort in information processing when both types of information are acquired. The results show that when justification is present, participants are less likely biased toward the app scoring higher on product impressions than when justification is absent. Thus, the motivational effect of more effort in information processing likely cancels out the negative effect of justification on acquiring both types of information in the absence of restrictions. The two possible countereffects of higher acquisition cost but more effort in information processing might cause the insignificant interaction effect on decision performance.

Supplemental Analysis

Underlying motives to prefer product impressions over customer problems

In the development of H1, I argue that decision-makers prefer product impressions over customer problems because it is essential for them to control issues with the new idea and to know if and how the new idea can be improved. To provide further evidence, I include three post-experimental questions in the experiment that relate to the importance of control and improvement for decision-makers. All three questions are measured on a 7-point Likert scale ranging from strongly disagree to strongly agree. I ask participants to what extent it was important to them to (1) control issues with the app (*control*), (2) be able to change issues with the app (*change*), (3) improve the app (*improve*). The results are shown in Table 7. All three measures show mean values above 5 (*control*: 5.36, *change*: 5.45, *improve*: 5.97) and a median of 6 indicating high importance to control issues and having the opportunity to change and improve the new idea. In addition, I run a one-way ANOVA. The results reveal that the coefficient of *Condition* is insignificant on all three measures (*control*: $F = 0.16$ $p = 0.921$, *change*: $F = 0.83$ $p = 0.478$, *improve*: $F = 1.10$ $p = 0.349$, two-tailed). Thus, the importance does not significantly differ across conditions. This indicates that decision-makers generally consider control over issues and the opportunity to make changes and improvements to be very important.

TABLE 7
Motives for Information Preference

Panel A: Descriptive statistics – Mean (standard deviation)

control	change	improve
5.36 (1.54) n=231	5.45 (1.57) n=231	5.97 (1.31) n=231

Panel B: Test across conditions – ANOVA

	df	MS	F	p
control	3	0.388863007	0.16	0.921
change	3	2.0559235	0.83	0.478
improve	3	1.89617424	1.10	0.349

Table 7 Panel A presents the descriptive statistics of the following three post-experimental questions: It was important to me to (1) control issues with the app (*control*), (2) be able to change issues with the app (*change*), (3) improve the app (*improve*). Panel B represents one-way ANOVA per question to test whether the importance for participants differs across conditions. * $p \leq 0.10$; ** $p \leq 0.05$; *** $p \leq 0.01$; p-levels are two-tailed.

Effects of feedback

After period 1, participants receive feedback on the WTP of the apps, their total return, and their bonus. To analyze learning effects, I investigate whether the information acquisition behavior changes between period 1 and period 2. This allows me to assess whether feedback mitigates the biases defined in the hypothesis development: (1) the general preference for product impressions over customer problems and (2) the acquisition of both types of information despite selective attention to product impressions. I report the results in Table 8. Panel A shows the frequencies of acquiring product impressions versus customer problems when one type of information is acquired. Panel B shows the frequencies of acquiring one versus both types of information. In both cases, I use McNemar $\chi 2$-tests to test the effects of feedback.

First, I investigate whether the acquisition shifts to information on customer problems from period 1 to period 2. A shift to information on customer problems indicates that decision-makers learn that acquiring product impressions is less optimal. In this case, the preference for product impressions is mitigated by learning effects. The results show that the frequency of acquiring customer impressions slightly increases from period 1 to period 2 but that this effect is insignificant (44.79% vs. 50.92%, $p = 0.302$). This indicates no change in preference in period 2, i.e. no learning effect between period 1 and period 2.

Second, I investigate whether the frequency of acquiring both types of information changes. As shown previously, in the absence of justification, decision-makers bias more likely to the app scoring higher in product impressions when acquiring both types of information. This is because, in case of contradicting information, decision-makers bias their attention to the information, which increases more likely their sense of control, i.e., they bias their attention more likely to information on product impressions. Thereby, decision-makers do not anticipate that they will not use both types of information equally but selectively. In case of a decrease in the frequency of acquiring both types of information, decision-makers would learn that acquiring both types of information will not pay off in the end. However, the results show that the frequency of acquiring both remains equal (36.07% vs. 36.07%, $p = 1.00$). Showing no decrease in acquiring both types of information indicates that this bias is not mitigated by feedback and learning effects. Decision-makers do not learn that acquiring both types of information will not pay off in case of contradicting information.

TABLE 8
Effects of Feedback

Panel A: Product impressions versus customer problems acquired – McNemar χ2-test

	customer problems	*product impressions*	*Total*
Period 1	44.79% n=73	55.21% n=90	100.00% n=163
Period 2	50.92% n=83	49.08% n=80	100.00% n=163
			McNemar χ2 (p): 1.06 (0. 302)

Panel A: Both versus one type of information acquired – McNemar χ2-test

	One type of information	*Both types of information*	*Total*
Period 1	63.93% n=39	36.07% n=22	100.00% n=61
Period 2	63.93% n=39	36.07% n=22	100.00% n=61
			χ2 (p): 0.00 (0.100)

Table 8 Panel A presents the McNemar χ2-test testing the effect of feedback on the frequency of acquiring product impressions compared to customer problems. The variables are *Period* and *AcqOne* (equals to 1 if product impressions is acquired and 0 if customer problems is acquired). The sample consists of participants acquiring one type of information in both periods. Panel B presents the McNemar χ2-test testing the effect of feedback on the frequency of acquiring both types of information compared to one type of information in the absence of acquisition restrictions and in the absence of justification. The variables are *Period* and *AcqBoth* (equals to 1 if both types of information is acquired and 0 if one type of information is acquired). * $p \leq 0.10$; ** $p \leq 0.05$; *** $p \leq 0.01$; p-levels are one-tailed.

V. Conclusion

In this paper, I investigate how restrictions in information acquisition and justification influence information acquisition and, consequently, decision performance in innovation budget allocations. In the experiment, participants are required to allocate budget among new ideas and, therefore, are required to acquire information on product impressions and/or customer problems. While feedback on product impressions is more commonly used in practice, prior literature states that managers should focus more on customer problems (Ulwick 2005; Wallace 2018). According to this literature, customers often buy products to solve a specific problem. Therefore, firms can enhance market success by providing tailored solutions to address these problems. Thereby the customer problem and the tailored solution should be the baseline for allocating budget, as the functional aspects can still be improved in case of lower scores after the budget is allocated. Thus, to decide whether a new idea matches a particular problem, prior literature argues that managers should gain information on customer problems instead of product impressions (Christensen et al. 2016a; 2016b; Ulwick 2005).

However, in this study, I show that managers generally prefer to acquire and process product impressions because they believe that this information increases their sense of control and consequently reduces the existing uncertainty in allocating budget in innovation. This preference reduces the probability of acquiring and processing information on customer problems. When acquisition restrictions are absent, managers are more likely to acquire both types of information in the absence of justification. However, due to their general preference, managers show selective attention to product impression information and ignore more likely information on customer problems. In a setting where the interpretation of market potential can be contradicting, as new ideas score higher on one type of information than the other, managers tend to overestimate the potential of new ideas scoring high on product impressions but low on customer problems due to their selective attention. This leads to lower performance when the restriction is absent than when it is present. In addition, I show that justification increases the likelihood that both types of information are acquired and thus acquisition cost, but it also leads to more effort in information processing, reducing the likelihood of selective attention. These two effects might counteract leading to an insignificant effect of justification in my study.

To test for a general preference, I design an experiment where participants choose between information that provides different insights but is cost-wise equal. Thus, I can provide controlled evidence that managers prefer product impressions, even if they can acquire customer problems at the same cost. Furthermore, this study provides insights into managers' information behavior and how it influences decision performance. I contribute to research on managerial accounting mechanisms in innovation. I show that unrestricted information acquisition does not lead to better decision performance in innovative budget allocation, as managers acquire both types of information but process the information selectively with regard to product impressions. However, justification can have a positive effect when both types of information are acquired by reducing selective attention.

In addition, I analyze learning effects in terms of information acquisition. Therefore, I run an experiment with two periods. Based on the results of this study, I cannot find a learning effect after participants receive feedback on their performance in the first period. However, some learning effects might materialize in the long term, i.e., after several rounds. Future research can investigate whether learning effects can occur in the long term by running an experiment with more than two rounds.

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Appendix

Experimental Materials:

Information on product impressions and customer problems

Definitions	
Information on Product Impressions	This customer feedback informs you about customers' impressions of the sport app's features. It indicates whether they liked the design and the features, and how easy they found it to use. All indicators are explained in more detail below.
Information on Customer Problems	This customer feedback informs you about whether customers face a specific problem that the sport app solves, how strongly their sport experience is affected by this problem and to what extent the app would solve the problem. All indicators are explained in more detail below.

Indicator	**Description**
Information on Product Impressions	
Excitement	the app is very unexciting (1) to very exciting (7)
Ease of Use	the app is very difficult to use (1) to very easy to use (7)
Design	the app looks very unappealing (1) to very appealing (7)
Clearness	not clear at all how to use the app (1) to very clear how to use the app (7)
Convenience	the app is very inconvenient to use (1) to very convenient to use (7)
Information on Customer Problems	
Degree of Problem	the problem that the app solves never (1) to frequently (7) occurs in customers' daily life
Level of Difficulties	due to the problem, customers experience no difficulties at all (1) to great difficulties (7) when doing sports
Complain Level	customers complain never (1) to frequently (7) about the problem
Improvement	the app would not solve the customers' problem at all (1) to would solve customers' problem to a great extent (7)
Solution Search	customers have not yet searched for a solution at all (1) to have already intensively searched for a solution (7) to the problem

Period 1: Product information

Community Train

Find other workout-lovers for joint online workouts

Select the location where you exercise, e.g., at the gym, at home, or outdoors. In addition, set the workout duration and intensity based on your current physical condition and select the available equipment you want to use.

Based on your information, workouts will be suggested. Select the one you prefer.

Find other users who have chosen the same workout at that time and get in touch with them by checking their profiles and chatting or video chatting with them. After contacting them and deciding to exercise together, you can start your joint workout and share your experience.

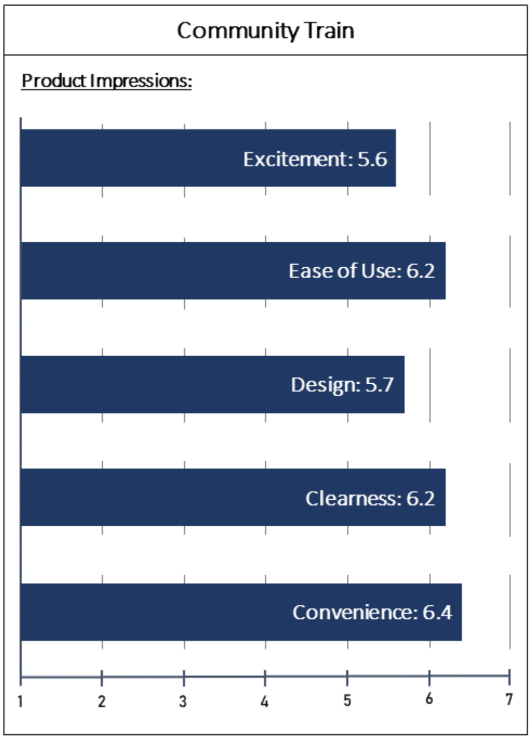
Train&Adapt

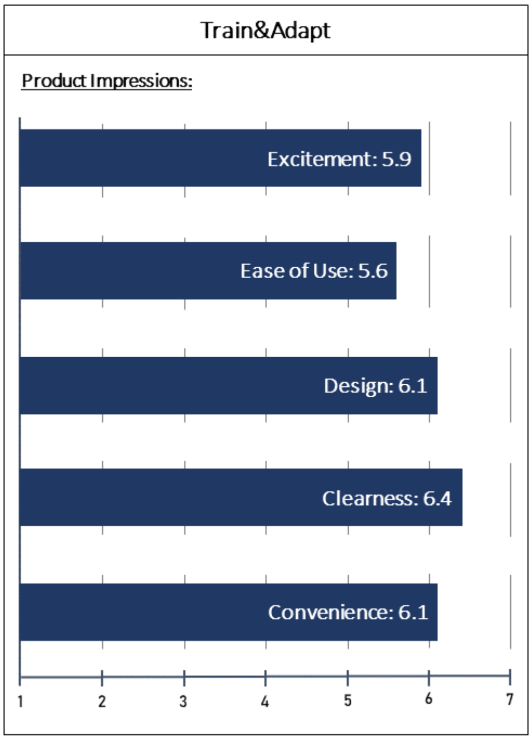
Adjust the exercises during the workouts

Follow the video instructions for your workout. During the 15-second break between exercises, you can decide whether you want to continue with or without equipment and whether you prefer a different intensity or exercise duration so that the next exercises will be adjusted. If you don't want to adjust anything, just take a 15-second rest and follow the upcoming workout instructions.

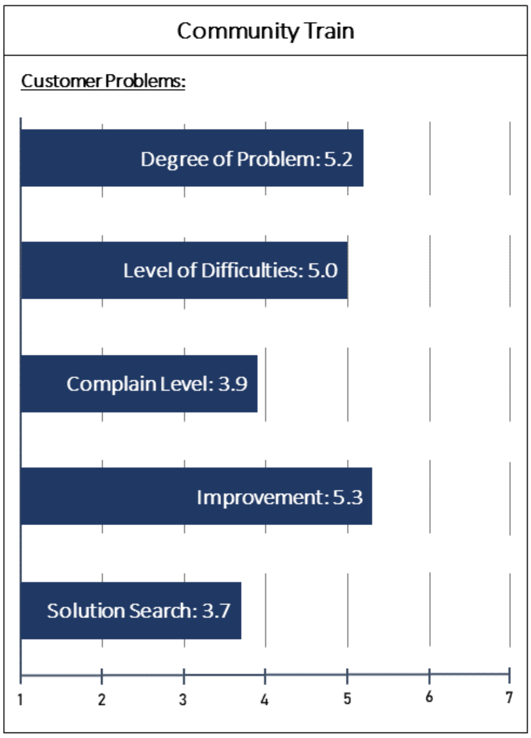
Rate the exercises during or after the workout. The exercises in the current workout and of upcoming workouts will be adjusted according to your likes and dislikes.

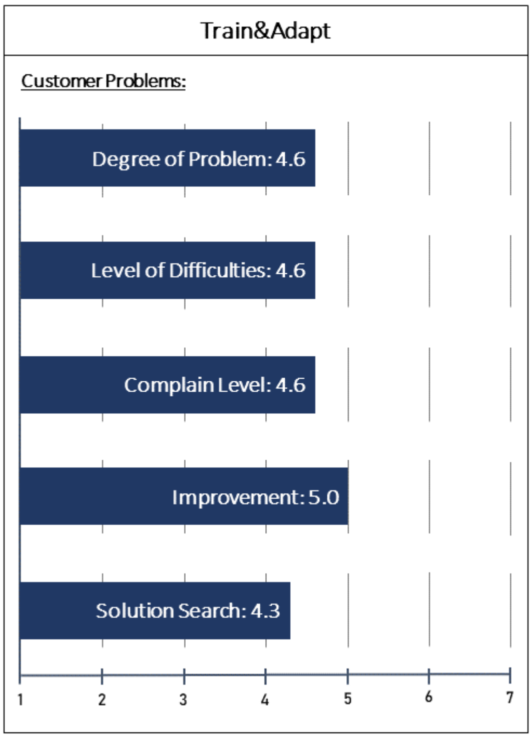
Period 1: Market Information – Product Impressions





Period 1: Market Information – Customer Problems





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Ich erkläre hiermit, dass ich diese Arbeit selbständig verfasst und keine anderen als die angegebenen Quellen benutzt habe. Alle Koautorenschaften sowie alle Stellen, die wörtlich oder sinngemäss aus Quellen entnommen wurden, habe ich als solche gekennzeichnet. Mir ist bekannt, dass andernfalls der Senat gemäss Artikel 36 Ab-satz 1 Buchstabe o des Gesetzes vom 5. September 1996 über die Universität zum Entzug des aufgrund dieser Arbeit verliehenen Titels berechtigt ist.

Bern, 09.09.2024

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