V-PONI: A Framework for Value-in-use Predictions Based on Obtaining Non-precise Indicators

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Abstract. *This paper presents an approach to address the practical and academic challenge of predicting the success of technologies in advance. The main contribution is the conceptual development of a framework that enables predictions of value-in-use based on weak indicators that are derived from technology acceptance research. The components of the framework are developed in a multidisciplinary approach based on the design science principles that ensure rigor and relevance of the research process and its outcome. A preliminary evaluation agenda is presented to evaluate the framework regarding its viability and its usefulness in practice.*

Keywords. Technology acceptance, weak signals, predictive power

1 Introduction

Predictions of usage are an important topic for both, academia and practitioners, in the field of mobile technologies. Practitioners seek to reduce uncertainty regarding the future success of specific mobile services and products in order to avoid market failures. The scientific community on the other hand aims at providing models of technology adoption, acceptance or continuance with high explanatory power in order to reduce this uncertainty. Technology acceptance research was considered to be a very mature field of research for a long time. The predominating paradigm and its dominant model – the technology acceptance model (TAM) [9] - have been evaluated and re-evaluated to an extent that led some researchers to the assumption that we know everything about technology acceptance to almost certainty [5]. Recent work did reveal certain shortcomings of the state of the art in the field that necessitate further research on the topic of technology acceptance:

- Explanatory power is not necessarily equal to predictive power. This is particularly important when the dependent variable is a construct, e.g. “behavioral intention”, that intends to further predict usage. The limited predictive power of intentions has been addressed in previous studies (e.g. [21]).
- A related challenge is the choice of dependent variables. “Behavioral intention” is the most commonly used variable in acceptance research. As suggested by decision making theories, there are various steps between intention formation and actual action and these steps are influenced by a plethora of aspects [3]. The choice and level of definition of the dependent variable determines the research outcome as the lack of a meaningful dependent variable results in speculative research [13].
- Questionnaire-based studies are dominant in the field. These belong to the reactive data collection methods whereas non-reactive or unobtrusive data collection methods eliminate the influence on user behavior [8].
- A variety of method biases, e.g. common method bias, reflective vs. formative measures etc. that are related to questionnaire-based studies is reported in the context of technology acceptance research [4].

The main research goal is, thus, the conceptualization of a framework that enables predictions of a valid dependent variable based on pluralistic non-reactive data collection methods to overcome the shortcomings of present approaches. The framework is developed according to design science principles using an iterative research design. Theoretical contributions to the development are drawn from technology acceptance research projects that addressed one or more of the challenges named above and other disciplines that utilize different forms of indicators to obtain predictions.

The remainder of this paper is organized as follows: Section 2 describes the applied methodology, followed by the conceptual development of the framework. The framework itself is outlined in section 4 and discussed in the subsequent section. The paper concludes with some general remarks and a research agenda for the application and evaluation of the framework.

2 Methodology

In order to ensure that both the research process and its outcome are scientific, the design science methodology suggested by Hevner et al. [16] was adopted as it has been successfully applied in various comparable projects, e.g. in [11] for the development of a business intelligence framework. The methodology provides seven guidelines for high-quality design science research in information systems research:

1) Design as artifact: The conceptual methodological framework V-PONI (value-in-use prediction based on obtaining non-precise indicators) is an artifact that addresses the task of non-reactive data tracking and observation in order to detect non-precise indicators with the aim of predicting value-in-use. The framework is generic and can therefore be used for various research projects and different data sources.

2) Problem relevance: As discussed in the introduction, there are a number of shortcomings in the current technology acceptance state of the art. For example, the shift to creating a framework with predictive power instead of focusing of the explanatory power of a model creates valuable insights for innovating technologies or technology products and their evaluation.

3) Design evaluation: The V-PONI framework is still conceptual, yet there is a clear evaluation approach to verify its viability that is based on signal detection theory and the ROC curve. Evaluation of usefulness in practice of the framework in a number of case studies is a second step in this area. A first exemplary appliance of the framework will be showcased in the subsequent chapters.

4) Research contribution: The main contributions of this research are the demonstration of the general feasibility and practical usefulness of application of the framework for predicting value-in-use through detection of weak signals. The obtained results aim at advancing the field of technology acceptance research through counterbalancing of certain shortcomings by introducing novel methodological approaches.

5) Research rigor: As the research was performed as an interdisciplinary project the creation and evaluation were based on the knowledge base of several academic disciplines and follow their specific rigorous requirements. Technology acceptance research and value-in-use research are embedded in the field of information systems research and are also rooted in the field of cognitive psychology. The detection of weak signals is an important issue not only in the field of business intelligence but also in trend analysis and terrorist detection.

6) Design as a search process: Existing artifacts were analyzed in order to obtain information from several sources that in combination improved the quality of our search for the most useful models for the present purpose. Additionally, the creation of the framework was conducted in iterative cycles [16] and the automated approach incorporates cycles of machine learning.

7) Communication of research: It is intended to communicate this research to academics and practitioners in order to stimulate further research on this topic and at the same time enable easy application of our results to practical issues.

3 Conceptual development

Previous research focused on predicting value-in-use is scarce as the concept of value-in-use originates from service-dominant logic whilst technology acceptance comes from a very product-driven environment. There is still a lack of interdisciplinary exchange that leads to a holistic approach which we attempt with the V-PONI framework.

A number of studies dedicated to the prediction of consumer-perceived value have been conducted; however, the focus is generally laid on service-related fields (e.g. [28]). Other studies on the prediction of customer behavior build upon value as providing the leading indicators [14], ergo using different value dimensions such as emotional value, functional value etc. as indicators for (mobile) technology use and usage continuance.

The major challenges in predicting future usage have been addressed in different fields of research. Firstly, technology acceptance research, and the related disciplines adoption research and continuance research, provide approaches to improve the predictive power of their results as well as mitigate the consequences of inherent challenges. These conceptual components are integrated in the theoretical corner stones of the framework. Further contributions are derived from existing literature and methodologies originating in disciplines that make use of non-precise indicators or weak signals as well as research of value perception. Additionally, previous research on value-in-use originating from different research streams that deal with the perception, importance and application of value such as the e-commerce, financial and strategy stream [1] contributes to the framework.

3.1 Approaches from technology acceptance research

Recent developments in the context of TAM focused on practical implications rather than pure explanation of usage intention. The presentation of TAM3 [33] came along with a research agenda on interventions that organization can implement to foster actual usage of technologies. The authors state that there is a need for further research on actual implementation and design issues when evaluating technology acceptance.

Further research requires, however, input from other fields that offers novel approaches of tackling current TAM related challenges. The aspects of usage contexts and their relevant dynamics [20] form the context for value-in-use as introduced in service-dominant and also customer-dominant logic [32; 14]. According to this research stream, value can only be produced in a certain context and "behavioral intention" is not able to fully explain whether a technology is accepted and used or not. Value-in-use describes value creation as a consumer-initiated process: Value is created or co-created with the selling or providing organization through the use or consumption of a product or service, thus making value a relational, dynamic and very subjectively perceived construct that may vary from one customer to another [34; 19]. The value-in-use construct has been transferred into a mobile context in form of the concept of mobile value core [27]. The mobile value core defines the intersection of provider expectations/offer and user expectations/perceptions as the realized value of mobile products and services. The concept involves contextual information and relationships between value forming processes on both sides.

Information system continuance research addresses the methodological shortcoming of technology acceptance studies that are based on one-shot surveys. The introduction of expectation-disconfirmation theory to continuance research [6] necessitated a shift towards longitudinal studies with several points of data collection. The separation of data collection points also mitigates the occurrence of common method bias. More recent studies indicated a need to measure conformation (or disconfirmation respectively) not directly as suggested in prior studies but separately as the difference between expectation and experience with technology usage in order to further avoid joint effects [33]. Others suggest the utilization of independent data sources as the "virtually only way" to avoid common method bias [31].

Non-reactive methods of data collection have been applied to acceptance research tasks in recent research projects. Content analysis was used to extract motives from user reviews regarding successful technologies in order to enable continuous automated acceptance monitoring [29]. Other unobtrusive methods that were applied to similar tasks, such as user experience research or usage pattern evaluation, are shadowing, user tracking etc. However, the pluralist methodology as suggested by Mingers [25] has not jet replaced the methodological paradigm in acceptance research.

3.2 Contributions from non-precise indicator research

Strategic management research utilizes weak signals to foresee discontinuities in a branch or on the market in general [2]. These weak signals are considered to be imprecise indicators of potential, highly effective events. In contrast to traditional strategic planning that requires strong signals, the vague content of weak signals is used to gradually respond to them. Weak signals for managerial decision making are obtained from a pre-defined range of typical weak signals that can be expected in the context of a specific discontinuity [2].

Future studies base their predictions on weak signals from different sources and emphasize the necessity to combine different data sources in order to obtain weak signals [18]. Other forecasts use price mechanisms from prediction markets as a method to generate predictions based on the wisdom of crowds [23].

Security and intelligence research applies weak signal analysis to the task of terrorist detection. Automated systems of terrorist detection are often based on analysis of digital traces for the behavioral markers that indicate terroristic potential. The implementation of such a system requires an analysis model that includes hypothesis regarding manageable sub-problems that are later aggregated to identify a potential terroristic threat by means of automated text analysis [9]. This approach is similar to the exploration of the possible range of weak signals as suggested in strategic management literature.

Semantic trend detection is another field of research that is using the same methods for the classification and interpretation of text chunks on the web as intelligence research. Twitter posts and other sources of textual data on the web have been utilized to predict particular events in the past. An example is the prediction of stock markets by means of sentiment analysis in twitter postings [7]. Similar techniques have been applied to monitor a wide range of web data in order to extract semantic weak signals, so called innovation signals [24]. The innovation signal approach involves iterations that are used to adapt search terms and fields over time. This iterative approach enables continuous improvement of the detection mechanisms and their outcome.

4 The V-PONI framework

The V-PONI framework consists of four layers as depicted schematically in Fig. 1, which are designed to execute the shift from explaining behavioral intentions to predicting value-in-use:

- Indicator layer
- Data layer
- Analysis layer
- Prediction layer

In a first step, the indicator layer, it is necessary to broaden the range of possible indicators for value-in-use. Results from technology acceptance research, technology adoption research and continuance research are utilized to define search fields and keys. The indicators are obtained by screening empirical studies for significant acceptance factors, which are considered as potential predictors of value-in-use. Unlike traditional explanatory models this layer includes acceptance factors from different models as the intention is to reduce divergence loss of value-in-use predictions. Divergence loss would be increased if the screening process was limited to empirical studies from a particular stream of technology acceptance research. For instance, the exclusive consideration of TAM-based models will leave out cost-benefit related or hedonic value-in-use and many other sources of value-in-use. The intermediary result is a comprehensive list of indicators which achieve significant results in explaining acceptance of any technology. These indicators can be either weak or strong in their predictive power.

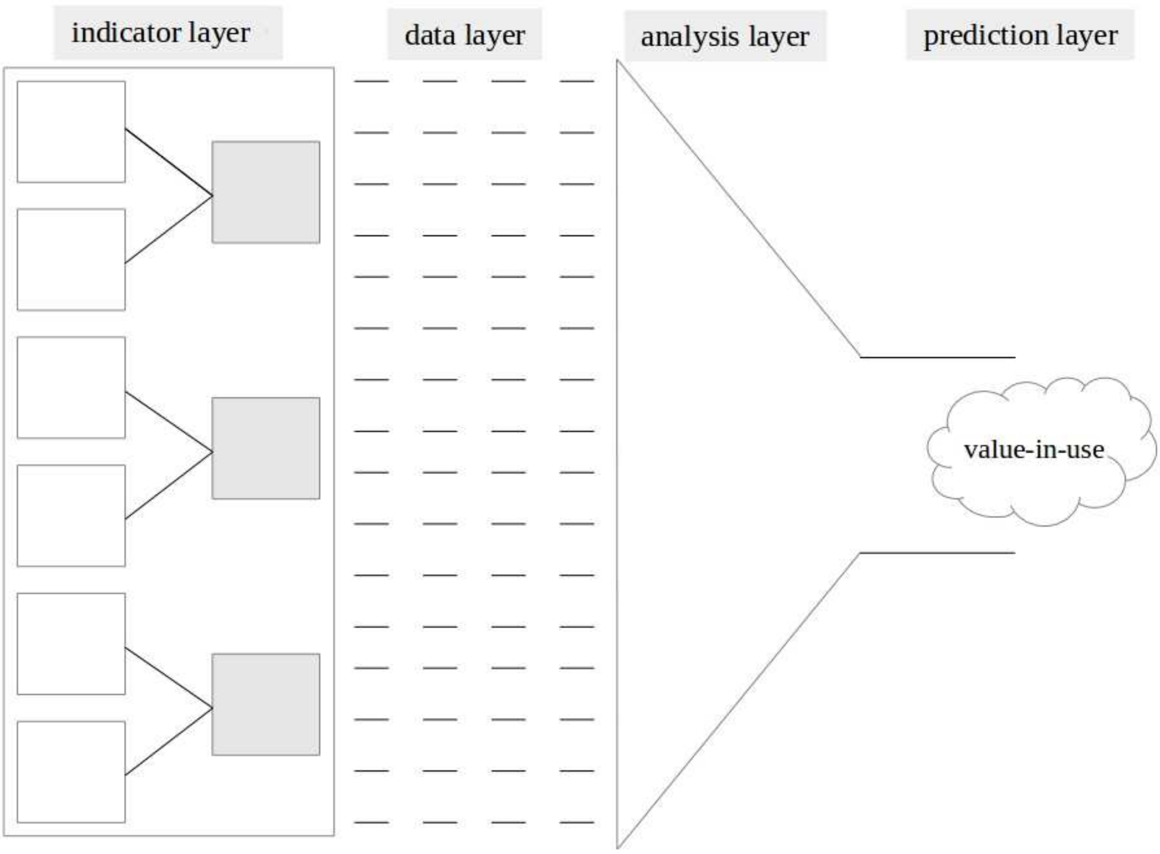

Figure 1. Schematic visualization of the V-PONI framework

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The next step is collecting data for these indicators. As recommended in prior research the focus is on non-reactive data collection methods. Data tracking, secondary content analysis and observation are chosen due to their non-reactivity and the opportunity to enable at least partially automated data collection. Automation is preferred as non-precise indicator detection requires continuity in monitoring data. Different data sources may necessitate different operationalizations of indicators, and thus, achieve different results. Method triangulation (e.g. a combination of tracking two different data streams or observation and secondary content analysis) is recommended to overcome this challenge and to obtain meaningful results.

The subsequent data analysis requires automated processing. Automated approaches support the identification of weak and strong indicators of value-in-use from the noisy data that is collected. Huge amounts of data are obtained from continuous data collection. They need to be analyzed promptly to be useful in practice. As prior research indicated that acceptance factors change dynamically it is probable that value-in-use predictors change over time as well. Consequently the data analysis has to be adaptive and enable dynamic changes of input, i.e. additional indicators from current empirical studies, real-time differentiation between weak and strong indicators, and predictive values of each indicator. Indicators are added to the indicator layer manually whenever novel significant acceptance factors are published. Real-time differentiation between weak and strong indicators is achieved by means of machine learning. Semi-supervised learning with chronologically shifting training data sets will enable the adaptive changes. The same procedure is applied to the detection of indicators, which are relevant to value-in-use in general.

Ensuring a viable prediction of value-in-use requires an evaluation of whether the factors collected in the prior processes indeed occur together with value-in-use as well as the extent to which the collected factors correlate and co-influence the dependent variable. For this purpose the receiver operating characteristic (ROC) from signal detection theory provides a useful evaluation matrix. ROC curves depict the performance of binary classification tools. Computing a ROC curve for each indicator will, thus, result in levels of predictive power. These levels are aggregated in form of actual value-in-use predictions based on the occurred indicators and their respective predictive power levels.

4.1 An example showcase of V-PONI application

The V-PONI framework is exemplarily outlined assuming that one wants to market a novel mobile payment application. An extensive literature review on adoption, acceptance and usage of mobile payment (like e.g. [26]) is conducted in order to obtain possible indicators. For the purpose of the example showcase the indicator list is obtained from only three papers [10], [22], and [30]. Trust is suggested as an indicator of ease of use and usefulness that further lead to the adoption intention of mobile payment systems [10]. In the respective model trust is influenced by characteristics of mobile service provider (reputation and opportunism) and characteristics of the mobile technology (environmental risk and structural insurance). Age, gender, mobile internet usage and internet banking usage were tested as control variables. The research model in the second analyzed paper [30] also includes trust, ease of use, and usefulness as indicators but in different cause-effect relationships. These are neglected for the further procedure. Shin et al. [30] also include social influences, perceived security and self-efficacy in their research. Gender, age and income serve as moderators. In the third study [22] trust is further deconstructed into internet payment trust and initial mobile payment rust. The splitting is ignored for the further processing of the indicator list. Moreover the model includes perceived cost and perceived risk as negative valences for the behavioral intention, and relative advantage, compatibility and image as positive valences.

Data collection is performed based on the indicator list. In the course of the exemplary showcase a random sample of ten indicators was chosen from the three papers. For an actual prediction all indicators would be used in this step to avoid a loss of predictive power. In order to obtain meaningful data it makes sense to utilize different data sources and collection methods as outlined in table 2. Indicators that are difficult to tackle or complex will require method triangulation.

Table 1. Possible Indicators And Data Collection Methods For Mobile Payment Value-in-use

Indicator	Data collection
Trust [10], [30], [22]	• Sentiment analysis of social media content; key terms: trust, trustworthiness, trustfulness, faith etc. • Observation of experiment with showing/non-showing certificates indicating trustworthiness
Ease of use [10], [30]	• Content analysis of user reviews; key terms: easy, fast, quick, hard, complicated, laborious etc. • Clickstream analysis; drop-outs during payment process
Service provider reputation [10]	• Sentiment analysis of social media content; key terms: provider names etc. • Observation of provider change behavior among customers
Age [10], [30]	• User account data
Gender [10], [30]	• User account data
Mobile internet usage [10]	• Analysis of log-data • Browser history analysis
Internet banking usage [10]	• User account data • Survey data
Social influences [30]	• Data of friends (obtained from social media) who also use the service
Relative advantage [22]	• Content analysis of social media and user reviews; key terms: better than, easier than, etc. and provider and product names • Observation of user behavior in the field
Compatibility [22]	• Analysis of user-owned devices, software, and bank products (e.g. credit card)

	• Comparison of general shopping history and availability of the new application

The obtained data is now analyzed by means of pattern recognition. The result of this step is probabilities for each indicator that it will result in usage, which can be further utilized for a machine learning model. A support vector machine will be used as normal distribution of data cannot be assumed. Following to that a field test of the newly developed mobile payment application is conducted and data collection methods that were defined in the data layer are applied to the sample. Predictions of value-in-use are made based on the application of machine learning model obtained from analysis on the data from the field test. The evaluation of the predictions takes place after market launch of the mobile payment application. Actual usage data is required to evaluate the accuracy of the predictions from V-PONI.

5 Discussion and outlook

The framework presented in this paper is a conceptual approach the predicting the success of technologies in advance based on non-precise indicators. The V-PONI framework offers a funnel approach. Its strengths lie in gathering data based on indicators derived from a multitude of sources, thus reducing divergence loss and enabling an observance of not only strong indicators but also weak indicators. The framework is dynamic, thus open to subsequent inclusion of new or adapted models in the indicator layer. Employing value-in-use as the dependent variable supports the intended shift from explanatory to predictive power.

Value-in-use proves an adequate and valid dependent variable for evaluation as it is subjective and dynamic based on different contexts in its nature. Changes in context induce changes in value-in-use and multiple changes in various context factors produce a complex transformation of the value-in-use as an outcome. However, it is this complexity of context factors – both external and internal – that requires substantial interdisciplinary research efforts.

It will be necessary to evaluate the V-PONI framework regarding both, the ability to predict value-in-use and its perceived usefulness in practice. The ability to predict value-in-use is related to the co-occurrence of detected indicators and value-in-use. The evaluation tackles two important dimensions, firstly, the correct detection of pre-defined indicators, and secondly, the correctness of indicators. The detection of pre-defined indicators is performed by means supervised machine learning. Traditional evaluation metrics, i.e. accuracy levels (F1) involving precision and recall of the implemented algorithm will indicate its ability to correctly detect pre-defined indicators. The second part of the evaluation is more sophisticated due to the complexity of value-in-use measurement. The evaluation of the co-occurrence of indicators and value-in-use will also utilize assessment methods from signal detection theory, which enables classification of a two-class prediction problem (see table 2) in this case the prediction or non-prediction of value-in-use based on detected indicators.

Table 2. Evaluation Matrix For Value-in-use Predictions

	value-in-use positive	value-in-use negative
value-in-use predicted	true positive	false positive
value-in-use not predicted	false negative	true negative

The result will indicate the preliminary ability of the framework to predict value-in-use correctly. In case of unsatisfying results there are several options to improve the performance. The accuracy of the machine learning algorithm can be improved by providing an extended training data set. The addition of further positive and negative examples for indicators will result in better indicator detection performance. High levels of false positives in the subsequent evaluation of value-in-use predictions can be mitigated by re-assessments of predictive power levels of single indicators. Providing further data from other data sources might also improve the imbalance. False negatives can be addressed by adjustments of the indicator layer. Additional potential indicators of value-in-use can be obtained from inclusion of further explanatory models.

The second dimension of the V-PONI framework evaluation, its usefulness in practice, will be addressed in a field study. Prototypical implementations in selected companies from different branches will provide information regarding the acceptance of the predictions. The evaluation will emphasize perceptions regarding the value of provided results.

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