Unified Theory of Acceptance and Use of Technology (UTAUT) for Intelligent Process Automation

Alexander Mayr
TU Dortmund, alexander2.mayr@tu-dortmund.de

Philip Stahmann
Technical University of Dortmund, philip.stahmann@tu-dortmund.de

Maximilian Nebel
TU Dortmund, maximilian.nebel@tu-dortmund.de

Christian Janiesch
TU Dortmund University, christian.janiesch@cs.tu-dortmund.de

Unified Theory of Acceptance and Use of Technology (UTAUT) for Intelligent Process Automation

Completed Research Paper

Alexander Mayr
Paxray GmbH
Würzburg, Germany
a.mayr@paxray.com

Philip Stahmann
TU Dortmund University
Dortmund, Germany
philip.stahmann@tu-dortmund.de

Maximilian Nebel
TU Dortmund University
Dortmund, Germany
maximilian.nebel@tu-dortmund.de

Christian Janiesch
TU Dortmund University
Dortmund, Germany
christian.janiesch@tu-dortmund.de

Abstract

Intelligent process automation is a technological innovation that combines symbolic automation tools with machine learning. Intelligent process automation can automate complex tasks that otherwise have to be performed by humans when symbolic automation is not powerful enough. Regardless of the high economic potential for companies, the adoption rate in practice is comparatively low. This could be due to the adoption behavior of the employees. In our work, we iteratively develop a Unified Theory of Acceptance and use of Technology (UTAUT) model for the adoption of intelligent process automation and evaluate it with an empirical study. With our research we want to empower designers to adapt the corresponding tools in the future to increase adoption. The study shows that, in addition to established factors for technology adoption, trust, transparency, and attitude towards technology are primary decision factors.

Keywords: Intelligent Process Automation, UTAUT, Technology Adoption

Introduction

There is a general consensus in research and practice that artificial intelligence (AI) offers huge transformation potential for organizations in all industries (Grashof and Kopka 2022). The automation of processes in particular offers opportunities for optimization and increased efficiency (Chakraborti et al. 2020). Organizations typically use symbolic process automation, which comprises business process management (BPM) and robotic process automation (RPA) (Herm et al. 2021). These approaches only enable automation of highly standardized, transaction-intensive processes based on explicit sequence flows and decision rules (Asatiani and Penttinen 2016; Fersht and Slaby 2012). Due to these restrictions a significant portion of practical business processes cannot be automated with symbolic process automation and therefore are subject to cost-intensive and error-prone manual steps (Chakraborti et al. 2020).

Intelligent process automation (IPA) complements symbolic process automation with AI technology, which mimics human cognitive abilities (Janiesch et al. 2021). Enhanced by AI, the IPA toolbox spawns promising opportunities to automate complex processes that require cognition and had to be performed by human agents prior. IPA approaches may be useful in tackling sophisticated process steps such as evaluation, reasoning, decision making, and process fulfillment (Chakraborti et al. 2020; IEEE 2017). IPA can automate complex tasks such as image and natural language processing, optical character recognition, prediction, or reasoning and consequently increase efficiency and result quality (Herm et al. 2021).

Although IPA can represent an essential aspect for organizations to ensure their relevance and competitiveness, many organizations are not implementing these solutions on a large scale (Jyoti and Szurley 2021). The low adoption of technologies in general can intuitively be broken down to inhibited successful implementations in individual organizations, which in turn has been shown to be highly dependent on individual employee adoption of technologies (Venkatesh and Bala 2008). This raises the question as to which factors determine IPA adoption by employees. To investigate the determinants and from that identify implications that are likely to increase the adoption rate of IPA, we formulate the following research question:

RQ: *Which factors determine the adoption of intelligent process automation by employees?*

To answer this research question, we developed an extended UTAUT model and evaluated it in an iterative manner to identify potential determinants for the adoption of IPA. The remainder of this paper structures as follows. Section 2 outlines the theoretical background on symbolic and intelligent process automation. Section 3 covers the 5-step research design. Subsequently, Section 4 details the derivation of potential determinants for adoption. Our research model is presented in Section 5. The subsequent sections outline the results, discuss these, point out implications for academia and practice, and lastly draw a conclusion.

Theoretical Background

Symbolic and Intelligent Process Automation

Processes represent interrelated events, activities, and decision points by which a set of actors interacts with physical or intangible objects. Business processes lead to an output that has a quantifiable value for at least one consumer or a company. The activities can be subdivided into smaller tasks. The sequence of these tasks is determined at defined decision points from potential process variations (Dumas et al. 2018).

Processes can be categorized by frequency and variance (van der Aalst et al. 2018). Following the Pareto principle in the context of organizational decision making, usually about 20 % are automated by traditional symbolic process automation. Processes that involve repetitive tasks but do not have a frequency high enough for traditional BPM are potentially subject to RPA. The third category covers processes with a low frequency as well as a high deviation from the norm and usually need to be handled by humans (van der Aalst et al. 2018). To leverage potentials in terms of time and cost reductions with symbolic BPM and RPA, certain process criteria need to be met. These include a high degree of standardization, no or few exceptions, the divisibility into simple and unambiguous rules, a sufficiently large volume of transactions, and low or no interaction with human workers (Asatiani and Penttinen 2016; Fersht and Slaby 2012). Regardless of the approach, the implementation needs to be carried out in a symbolic manner automated by formulating explicit sequence flows and decision rules (Asatiani and Penttinen 2016; Fersht and Slaby 2012). The approaches mentioned can be summarized under the term *symbolic process automation* (Herm et al. 2021). However, a significant portion of business processes cannot be automated as they are subject to cost-intensive and error-prone manual steps (Chakraborti et al. 2020).

IPA (IEEE 2017), also known as hyperautomation (Gartner 2019) or cognitive automation (Engel et al. 2022), subsumes approaches to potentially overcome the imperfections of symbolic process automation. IPA represents software robots that combine the methods of symbolic automation with the benefits of AI. The combination enables automation of complex processes and tasks that otherwise must be completed by humans. A real-life example of IPA are processes with a large number of decision variables, from simple tasks such as invoice verification (which usually has to be carried out entirely by humans) to complex tasks such as enabling sharing data within data trust models. These can be taken over completely or to a large extent (like invoice or request recognition, pattern recognition, or automatic creation of confirmations and overdue notices in the case of invoice verification) by intelligent software agents. This is made possible by advances in machine learning and deep learning (Janiesch et al. 2021), which enable systems to process information corresponding to human cognitive abilities (Herm et al. 2021).

Unified Theory of Acceptance and Use

In IS adoption research, the Unified Theory of Acceptance and Use of Technology (UTAUT) developed by Venkatesh et al. (2003) has proven to be effective in different technologies and contexts (Hsu et al. 2014). It was developed by unifying several established technology acceptance models, including Theory of

Reasoned Action (TRA) (Davis 1989; Sheppard et al. 1988), Technology Acceptance Model (TAM) (Davis 1985; 1989), Motivational Model (MM) (Davis et al. 1992; Vallerand 1997; Venkatesh and Speier 1999), Theory of Planed Behavior (TPB) (Ajzen 1991), Combined TAM and TBC (C-TAM-TPB) (Taylor and Todd 1995), Model of PC Utilization (MPCU) (Thompson et al. 1991; Triandis 1977), Innovation Diffusion Theory (IDT) (Moore and Benbasat 1991; 1996), and Social Cognitive Theory (SCT) (Bandura 1986; Compeau and Higgins 1995). In its basic form, the UTAUT model consists of ten different constructs. These include *Usage Behavior* (UB), *Behavioral Intention* (BI), *Performance Expectancy* (PE), *Effort Expectancy* (EE), *Social Influence* (SI) and *Facilitating Conditions* (FC). The moderators of the model include *Gender* (GDR), *Age* (AGE), *Experience* (EXP) as well as the *Voluntariness of Use* (VOU) (Venkatesh et al. 2003).

BI is defined as a measure of the prediction of any voluntary action unless the intention changes before actual execution or the measure of intention does not match the behavioral criterion in terms of action, goal, context, timing, or specificity (Sheppard et al. 1988). PE is defined as the extent to which the individual believes that using the system will help him or her achieve job improvements (Davis 1989). The five constructs from which PE is derived are *Perceived Usefulness* (TAM, TAM2, and C-TAM-TPB), *Extrinsic Motivation* (MM), *Job Fit* (MPCU), *Relative Advantage* (IDT), and *Outcome Expectations* (SCT). EE is defined as the degree of ease of use of the system. The three constructs from which EE is derived are *Perceived Ease of Use* (TAM and TAM2), *Complexity* (MPCU), *and Ease of Use* (IDT) (Venkatesh et al. 2003). SI is defined as the extent to which the individual perceives that significant others believe one should use the system. SI is represented as *Subjective Norm* in the TRA, TAM2, TPB, and C-TAM-TPB models, as *Social Factors* in the MPCU, and as *Image* in the IDT. FC is defined as the degree to which an individual believes that the organizational and technical infrastructure exists to support its use. The definition here derives from concepts of three different constructs from the original models of UTAUT. Specifically, these are the constructs *Perceived Behavioral Control* (TPB, C-TAM-TPB), *Facilitating Conditions* (MPCU), and *Compatibility* (IDT) (Venkatesh et al. 2003).

Research Design

This paper aims to identify determinants for IPA adoption and evaluate these using UTAUT to explore reasons for the low adoption rate of IPA in practice. Venkatesh (2022) proposes the model specifically for adoption studies of AI-based technologies. Our development of the extended UTAUT model as a potential solution to the identified problem is accomplished through three research methods. First, we derive potential determinants of adoption and their respective connections via a structured literature review, which we validate via expert interviews. Subsequently, we develop an extended UTAUT model. The measurement model is evaluated via experts and a preliminary study and optimized based on the outcome. We demonstrate the final model and evaluate it via an empirical survey. In the subsequent discussion of the results, we derive and communicate implications for research and practice.

Structured literature review. We conducted a structured literature review according to vom Brocke et al. (2015) to identify potential determinants for IPA adoption. We used the five databases EBSCOhost Business Source Premier, AISeL, ACM Digital Library, Web of Science, and IEEEXplore as these comprise high-quality outlets covering related IS research. We used the search string (("unified theory of acceptance and use of technology" OR utaut OR "technology acceptance model" OR "theory of planned behavior" OR "social cognitive theory" OR "motivational model" OR "theory of reasoned action" OR "Innovation diffusion theory" OR "social cognitive theory") AND ("business process management" OR "intelligent automation" OR "process automation" OR "artificial intelligence")). We considered scientific journals and conference proceedings in the analysis. Initially, we identified 2,441 publications. After removing duplicates and scanning abstracts and keywords, we reduced the corpus to 152 publications. In a full text analysis, we classified 67 papers as relevant to our research goal. Subsequently, we performed a forward and a backward search and identified 73 publications resulting in 225 publications overall. Of these, 79 contain specific research models in the context of technology acceptance. The remaining publications include general as well as specific research directly or indirectly related to IPA or technology acceptance. For the synthesis of the publications, we used the concept matrix-based method proposed by Webster and Watson (2002) which resulted in the identifiaction of potential determinants.

Expert interviews. The potential determinants were validated through four expert interviews. The structure of the interviews is based on the work of Herm et al. (2021). We decided to use a two-part interview consisting of a structured and a semi-structured part to make the subjective fit of the constructs directly quantifiable and comparable and, furthermore, to allow open-ended responses and to guide them with focused questions (Bell et al. 2022). These experts hold various roles in research (E1 and E2, both with high-profile publications in the IPA-related areas of adoption of AI-based technologies and RPA), as well as in practical application (E3 and E4) of IPA or related technologies, with experience ranging from 4 (E1, E2, E3) to 10 years (E4). First, we asked the interviewees for personal attributes such as their organizational role, focus of expertise, and years of experience. After that, the interviewees were asked to quantify their degree of familiarity in the areas of IPA, (symbolic) process automation as well as AI on a 5-point Likert scale (E1=5,4,5, E2=4,5,4, E3=3,5,4, E=4,4,2). The total duration of the interviews was 172 minutes, which were transcribed to 6,736 words. Subsequently, we presented the derived potential determinants for adoption to them. In the next step, the interviewees were asked to quantify the perceived relevance of the constructs on a 5-point Likert scale of increasing relevance to enhance comparability. This was followed by an isolated free discussion of the interviewees' perceived relevance of the constructs presented to adoption. The interviews were recorded and transcribed in a denaturalized manner (Azevedo et al. 2017). Due to the semi-structured nature of the interview and the associated context-bound responses, as well as the unambiguous nature of the answers given by the experts, no multiple coding was required.

Model design and development. An extended UTAUT model to explain the adoption on IPA was generated from the constructs and connections derived from the literature analysis. This procedure is proposed by Venkatesh (2022) for studying the adoption and use of tools based on AI. The modal was validated and extended by expert interviews (E1 and E2) and then iteratively validated, evaluated, optimized, and demonstrated through an empirical survey and associated structural equation modeling.

Survey. We demonstrated and evaluated the model through a structured online survey. We used prolific.co to recruit native English-speaking employees with daily touch points with digital processes from different organizations for model evaluation. Since IPA is a novel technology and may not be known to the participants in detail, we provided a comprehensive explanation of the concept before the survey and illustrated it with some real-life examples of observed and unobserved IPA bots. For the technical implementation of the survey, we used unipark.com. To counteract the problem of careless responses and the associated suboptimal data quality, we used an attention check (Pei et al. 2020).

Structural equation modeling. Partial least squares structural equation modelling (PLS-SEM) was used to relate the findings from the evaluation. PLS-SEM constitutes a solution for small sample sizes and complex models with many constructs and a large number of items (Hair et al. 2019a; Willaby et al. 2015). PLS-SEM also causes low bias in reflective measurement models, which approach zero at sample sizes of n=100 and above (Marko et al. 2016). The assessment of the results follows the guidelines by Hair et al. (2014) and Hair et al. (2019a). Accordingly, for the quality of the measurement model, we checked factor loadings, FL-Criterion, CA, CR, and AVE. We evaluated the structural model via VIF, R^2, and Q^2 criteria, and the relevance and significance of the path coefficients. The related calculations were performed via Smart-PLS 3 (Ringle et al. 2015). Bootstrapping with 500 resamples (Kock and Hadaya 2018) was used for iterative optimization of the model. For the final derivation of the model parameters, we used bootstrapping with 5,000 resamples (Hair et al. 2014).

Derivation of Potential Determinants of Adoption

We identified 13 potential defining constructs for IPA implementation. Thereby, all papers contained at least one construct of the basic UTAUT model according to Venkatesh et al. (2003) namely PE (n=71), BI (n=69), EE (n=64), SI (n=48), FC (n=36), and UB (n=27). In addition, various extensions of the model were made by adding the constructs of Trust (n=32), Attitude towards using IPA (n=25), Perceived Risk (n=25), Perceived Value (n=13), Hedonic Motivation (n=11), Transparency (n=8), and Anxiety (n=5). The number of determinants used in the publications varies between 2 and 10 constructs with an average of 5.49 constructs. Furthermore, the use of the moderators AGE (n=15), GDR (n=10), EXP (n=15), and VOU (n=4) could be observed. The use of moderators was omitted in 76 % of the papers. This is likely due to the generally infrequent use of moderators in research (Dwivedi et al. 2019). Consequently, we adopted all constructs of the UTAUT basic model. We adapted the potential determinants of IPA adoption to the context. The identified extensions are outlined in the following paragraphs.

Attitude Towards Using IPA (AT). AT is defined as a person's general affective reaction to using a system (Venkatesh et al. 2003). Here, AT encompasses all positive and negative feelings of an individual when performing a defined target behavior (Ajzen and Fishbein 1977; Dwivedi et al. 2019). The construct shows significant overlap with the constructs Attitude Towards Behavior (TRA, TPB, C-TAM-TPB), Intrinsic Motivation (MM), Affect Towards Use (MPCU), as well as Affect (SCT), which play a supporting role in the respective models (Venkatesh et al. 2003). The relevance of AT in explaining technology acceptance is widely undisputed in research. For example, it has been shown that AT can accurately predict behavioral intention in terms of BI. In general, this assumes that individuals develop the intention to perform behaviors toward which they exhibit positive AT (Dwivedi et al. 2017).

Perceived Risk (PR). PR is usually represented or measured as a multidimensional construct (Cunningham et al. 2005; Lee 2009; Stone and Grønhaug 1993). Due to the lack of a unified and generally accepted definition of PR in the IPA context, we used the risk dimensions *Performance Risk, Financial Risk, Social Risk,* and *Physical Risk* defined by Jacoby and Kaplan (1972) and cross-validated by Kaplan et al. (1974) with the addition of *Time Risk* by (Stone and Grønhaug) and *Privacy Risk* by Featherman and Pavlou (2003). The first extension is made due to high explanatory values of this extension of up to 90 % of the variance of risk (Stone and Grønhaug 1993). The second extension is used due to the high relevance of privacy in the AI context (Jin and et al. 2018). Furthermore, in line with Featherman and Pavlou (2003), all defined risk dimensions are evaluated together via the dimension *Overall Risk*. It can be assumed that IPA software generally does not pose a threat to the physical or mental integrity of the human agents interacting with them. In accordance with the work of Lee (2009) and Featherman and Pavlou (2003), the corresponding risk dimensions *Psychological Risk* and *Physical Risk* are not considered.

Trust (TT). TT originates from interpersonal research (Danckwerts et al. 2020). It encompasses a variety of possible definitions and associated dimensions, depending on the particular discipline or other conceptual properties such as the trust recipient under study (McKnight et al. 2011; McKnight and Chervany 2001). The technologies combined in IPA are classifiable as human-like as AI strives to mimic human cognitive processes. Studies also show that anthropomorphism, that is ascribing human characteristics to AI-enabled technologies, specifically autonomous technologies and the perceived intelligence of the artificial agent in these, plays a significant role in the perception of the respective technology (Li and Suh 2021; Wanner et al. 2022). Accordingly, interpersonal trust variables are used following the recommendation of Tripp et al. (2011). We consider trust regarding IPA with the dimensions *Competence, Benevolence,* and *Integrity* (Danckwerts et al. 2020; Qiu and Benbasat 2009).

Anxiety (AN). AN describes the sum of rational and irrational fears or anxieties that a person perceives about the actual or potential use of a technology (Maurer and Simonson 1984). It can take on different manifestations and can be considered a secondary drive that may involve different avoidance responses (Devi et al. 2016). AN may refer to specific information processing technologies such as computers (Cambre and Cook 1985). If the use of the specific technology is voluntary, the likelihood of abandonment is comparatively high among individuals with corresponding AN (Rohner and Simonson 1981).

Transparency (TY). In the context of AI, no generally accepted definition of TY exists (Shin 2021). Understanding how technologies generate outputs can be of similar importance in some use cases as the quality of the respective outputs themselves. For example, identifying the inner workings represents a highly relevant factor when AI-based technology is used as the basis for mission-critical applications (Chakraborti et al. 2020; Wanner et al. 2022). In practice, the applications of simple-to-interpret linear models are usually limited. A sufficiently high accuracy can often only be achieved with complex models with black-box properties (Herm et al. 2022; Kalimeri and Tjostheim 2020; Venkatesh 2022). Black-box properties can have a negative impact on the adoption of corresponding technologies (Crockett et al. 2020). TY can be divided into the *Understandability*, the *Observability* as well as the *Explainability* of the AI-based technology (Mesbah et al. 2019; Shin 2021).

Price Value (PV). The monetary costs of new technologies can be a barrier to the adoption of innovations (Kim and Shin 2015). This is due to the observable negative correlation between the perceived costs of a technology and the resulting usage behavior (Jianbin and Jiaojiao 2013). However, pure monetary cost is usually not a determinant in technology adoption (Venkatesh et al. 2012). Accordingly, these are often conceptualized together with their quality to determine the perceived value of a product. Venkatesh et al. (2012) define PV as consumers' cognitive trade-off between the perceived benefits and the monetary costs of the construct to be adopted. Since employees (in particular managers) often have defined monetary budgets or compensation models that are directly related to the expenses made, PV may influence users' intention and, thus, is a possible determinant of technology use.

Hedonic Motivation (HM). HM describes the fun or pleasure that results from the use of a technology. It has been demonstrated that this construct can have a direct impact on technology acceptance and use (Thong et al. 2006; van der Heijden 2004; Venkatesh et al. 2012). Suh et al. (2017) further emphasize that hedonic components are critical components in maintaining usage behavior.

None of the constructs derived by the literature analysis or their contained constructs were classified as irrelevant from the interviewed experts. This results from the numerical assessment of the relevance of the respective constructs as well as the verbatim statements of the experts. In addition to the absolute values, the respective median was evaluated. This metric is suitable for summarizing or evaluating the collected stand-alone Likert items with ordinal scale level (Boone and Boone 2012). All median scores *(PE=5, EE=2.5, SI=4, FC=4, HM=3, PV=4.5, AT=4, TY=2.5, PR=3.5, TT=4.5, AN=5)* are above the 2.0 threshold "more likely not relevant to adoption". Accordingly, all constructs are classified as potentially relevant. In summary, the assumed relevance of all derived constructs could be confirmed by the expert interviews. Based on this, the constructs are transferred to further model development.

Research Model

Based on the structured literature analysis in the previous chapter, we derived a research model that includes 13 potential determinants. Here, **UB** describes the actual usage behavior of agents in the context of IPA. The construct is defined accordingly as a direct indicator of IPA adoption (Eisser et al. 2020). **BI**, **PE**, **EE**, **SI**, and **FC** are adopted from the original UTAUT (Venkatesh et al. 2003). **AT** is defined as a person's general affective response to the use of IPA (Dwivedi et al. 2019). **PR** is defined as the sum of all perceived risks associated with the use of IPA. **TT** is defined as the degree of confidence or trust in the specific technology IPA. **TY** is defined as the degree to which a human actor can comprehend and understand the internal processes as well as the associated outputs of IPA (Dam et al. 2018). **AN** is defined as the sum of rational and irrational feelings of anxiety or fear that people experience when potentially interacting with IPA (Maurer and Simonson 1984). **HM** is defined as the pleasure or enjoyment that results from using IPA (Venkatesh et al. 2012). **PV** is defined as the cognitive trade-off between perceived benefits and monetary costs of IPA (Venkatesh et al. 2012). **PR** is defined as the sum of all perceived risks associated with the use of IPA. In the proposed research model, the **AGE**, **GDR**, and **EXP** moderators defined in UTAUT are adopted from Venkatesh et al. (2003). We removed **VOU** analog to UTAUT2 (Venkatesh et al. 2012). Based on the statements of the interviewed experts that the horizonal position of the respective potential user in the company hierarchy could have a strong influence on the acceptance of IPA (E1, E2, E4), we constructed the moderator Job Level (**JOL**) with the parameters *Top Management*, *Management*, *White Collar*, and *Blue Collar* (Dohmen et al. 2004; Harber et al. 1991). The hypotheses regarding the relations of the 13 potential determinants are presented in Figure 1.

In addition, we assume the following moderating effects: AGE, GDR, EXP, and JOL are assumed to moderate H3a (H3c), H3b (H3d), H9a to H9c (H9d to H9f), H10a (H10b), and H11a (H11b). Moderating effects of AGE, GDR, and EXP are assumed on H2a (H2d), H4b to H4d (H4f to H4h), H7a to H7e (H7f to H7j). AGE, GDR, and JOL are assumed to have moderating effects on H1a (H1c), and H1b (H1d). AGE and GDR are assumed to have moderating effects on H6a to H6c (H6d to H6f), AGE and EXP are assumed to have moderating effects on H4a (H4e). EXP is assumed to have moderating effects on H12a (H12b).

Measurement Model. The selection of items for the definition of the measurement model was done by different methods. The selection of items whose constructs are part of the basic UTAUT model was done in a multi-step process analog to the work of Wanner et al. (2021). The pre-selected items collected in the structured literature review were matched with the information obtained from the expert interviews and filtered accordingly. They were reduced (if equivalent but not identical items were derived) or confirmed by experts E1 and E2. The items for TT and TY were taken from McKnight et al. (2002), Choi and Ji (2015), and Shin (2021) and adapted in scope. The items for PR were adopted from Choi and Ji (2015), Dwivedi et al. (2017), and Featherman and Pavlou (2003). Each of the defined risk dimensions was queried with a separate item. The items for the PV and HM constructs were adopted from the reference work of Venkatesh et al. (2012), which in turn was based on the work of Dodds et al. (1991) and Kim et al. (2005). The potential suitability of the defined items of PR, PV, HM, and UB was confirmed by E1 and E2. Analog to Venkatesh et al. (2012), UB was quantified in terms of frequency of use with the item *"Please choose your usage frequency for using IPA"* on a 7-point Likert scale with the anchor points *1="never" and 7="many times per day"*.

All items of the latent constructs were queried by a 7-point Likert scale with the anchor points *1="strongly disagree"* and *7="strongly agree"*. The items for the survey can be conferred to in a digital appendix (Mayr et al. 2023).

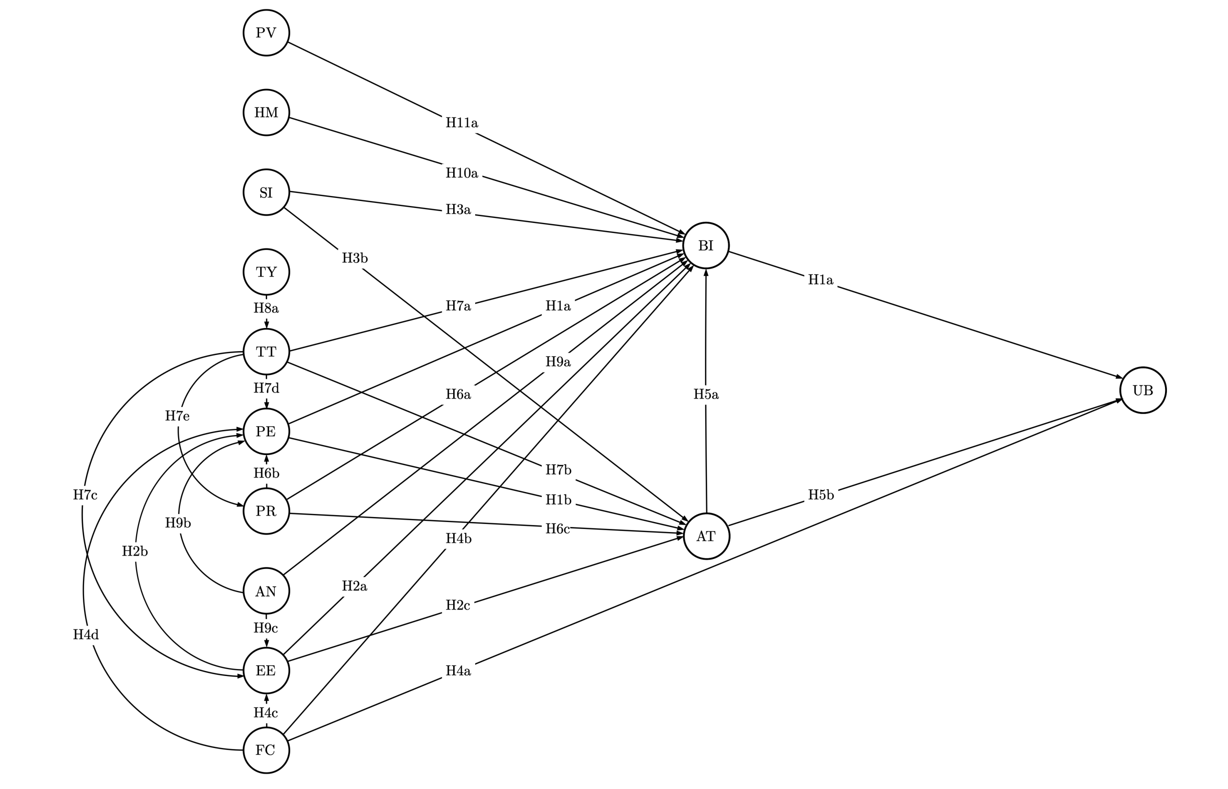

Figure 1. Hypotheses regarding the 13 potential determinants.

Pre-study. We conducted a preliminary study to test the measurement model beyond the factual derivation and expert survey. Participants were presented with a concise summary of IPA and the technologies it incorporates, as well as a hypothetical use case. The measurement model was thereby evaluated using PLS-SEM. In this regard, the tests conducted on the measurement model include checking internal consistency, convergent validity, discriminant validity, and reliability of the indicators (Hair et al. 2011). The preliminary study contained 21 valid treatments to successfully verify the items used.

Results

The sample of the main study is composed of subjects who are employed and use different technologies for their jobs daily. Pre-study participants were excluded from the main study to avoid survey bias. Out of 200 submissions, 168 were valid. The remaining subjects terminated the survey prematurely (*n*=29) or gave incorrect responses on the attention check (*n*=3). The appropriateness of the sample size was iteratively determined via the rule of 10 (Chin 1998) for the minimum sample size (*n*=100) and furthermore, based on the criticism of the sole reliance on this method (Hair et al. 2014), verified in Smart-PLS 3. Around 78.6 % of the participants were younger than 35. 42.9 % of the sample identify with female gender identity and 56 % with male gender identity, and 1.2 % with another gender identity. 40 % of the sample have experience with IPA or process automation in general. In each case, 53 people have between one and three years of experience with the technologies. 22.6 % of the respondents are part of the company's management. 56 % of workers surveyed are part of the white-collar cluster. The evaluation of the measurement model is carried out analogous to the preliminary study via the path coefficients CA, CR, and AVE. Analogous to Wanner et al. (2021) the minimum factor loading is set to 0.6. CA and CR should reach at least the 0.7 threshold and AVE should reach the 0.5 threshold. In addition, the FL criterion is to be met. Furthermore, for a comprehensive validity check, the measurement model is checked for cross-loadings as well as over the HTMT according to Henseler et al. (2015) and Hair et al. (2019b). The HTMT should not exceed the threshold of 0.85 (Voorhees et al. 2016). The final measurement model was defined by iteratively deleting the item with the lowest factor loading. The FL matrix emanating from them as well as the defined performance metrics CA, CR, and AVE are summarized in Table 1.

FL	AN	AT	BI	EE	FC	HM	PE	PR	PV	SI	TT	TY	CA	CR	AVE
AN	**0.7**												0.84	0.88	0.55
AT	*0.5*	**0.8**											0.92	0.92	0.71
BI	*0.3*	0.7	**0.9**										0.91	0.95	0.85
EE	*0.5*	0.5	0.5	**0.8**									0.86	0.92	0.78
FC	*0.3*	0.5	0.5	0.5	**0.7**								0.81	0.86	0.56
HM	*0.4*	0.6	0.5	0.5	0.3	**0.9**							0.93	0.95	0.87
PE	*0.3*	0.7	0.6	0.5	0.4	0.4	**0.8**						0.94	0.95	0.80
PR	0.4	*0.5*	*0.2*	*0.1*	*0.2*	*0.2*	*0.2*	**0.7**					0.71	0.82	0.53
PV	*0.2*	0.5	0.3	0.2	0.2	0.2	0.3	*0.3*	**0.9**				0.90	0.94	0.84
SI	*0.2*	0.4	0.5	0.4	0.5	0.3	0.5	*0.1*	0.2	**0.8**			0.86	0.90	0.70
TT	*0.4*	0.7	0.5	0.3	0.4	0.5	0.5	*0.5*	0.4	0.3	**0.7**		0.87	0.90	0.60
TY	*0.3*	0.5	0.5	0.5	0.4	0.4	0.4	*0.2*	0.2	0.2	0.5	**0.8**	0.71	0.84	0.63

Table 1. FL matrix and performance metrics of the main study with values <0 in italics.

The evaluation of the structural model was performed using different factors. It was optimized iteratively to match the defined performance metrics. All VIF values except AT on BI (5.3) were below 3. Due to the comparatively small difference to the defined threshold (5.0) and the literature-supported separation of the constructs BI and AT (Dwivedi et al. 2019), we assume a sufficiently high goodness of the structural model with respect to collinearity and the associated potential biases. We also checked R^2 (AT=0.75, BI=0.72, EE=0.48, UB =0.44, PE=0.42, PR=0.34, TT=0.26) and Q^2 (AT=0.51, BI=0.57, EE=0.33, PE=0.32, UB=0.38, PR=0.16, and TT=0.15).

Finally, we review the statistical significance and relevance of the path coefficients (Hair et al. 2019a). Based on this, of the defined hypotheses, we could confirm 14 completely and 3 proportionally. PE, EE, and TT have a significant positive influence on AT (H1b, H2c, and H6c). For the constructs EE, FC, and TT, significant positive effects on PE can be demonstrated (H2b, H4d, and H7d). In addition, a positive relationship between FC and EE can be identified (H4c). Furthermore, significant negative effects of PR on AT (H6c), of TT on PR (H7e), and of AN on EE (H9c) are present. BI is positively influenced by AT (H5a) as well as HM (H10a). TY has a direct positive effect on TT (H8a). The assumed positive correlation between BI and UB (H12a) can be confirmed. The respective path coefficients are shown in Figure 2. The moderating effects are not visualized to provide more clarity to the figure. None of the hypotheses related to the moderating properties of AGE, GDR, EXP, and JOL can be fully confirmed. Of the effects of AGE, GDR, and EXP on TT hypothesized in H7j, only the latter can be confirmed. Of the effects of all defined moderators between PV and BI assumed in H11b, a significant positive effect of JOL and a significant negative effect of EXP can be demonstrated. Furthermore, direct as well as statistically significant positive effects of EXP on EE (0.208*) and UB (0.411***) can be identified. All other hypotheses are rejected on this basis. Individual presentation of the associated path coefficients is omitted. The path coefficients are presented in Table 2.

Path	Coefficient	p-Value	Hypothesis	Support
PE → AT	0.321***	<0.001	H1b	yes
EE → PE	0.278*	0.0169	H2b	yes
EE → AT	0.169**	0.0078	H2c	yes
FC → EE	0.253**	0.0039	H4c	yes
FC → PE	0.198*	0.0223	H4d	yes
AT → BI	0.459***	<0.001	H5a	yes
PR → AT	-0.146**	0.0042	H6c	yes
TT → AT	0.382***	<0.001	H7b	yes
TT → PE	0.325***	<0.001	H7d	yes
TT → PR	-0.564***	<0.001	H7e	yes
TT * EXP → PR	-0.160*	0.0269	H7j	1/3
TY → TT	0.507***	<0.001	H8a	yes
AN → EE	-0.333***	<0.001	H9c	yes
HM → BI	0.144*	0.0462	H10a	yes
BI → UB	0.355***	<0.001	H12a	yes
PV * JOL → BI	0.146*	0.0172	H11b	2/4
PV * EXP → BI	-0.149*	0.0260	H11b	2/4
EXP → EE	0.208*	0.0368	-	-
EXP → UB	0.411***	<0.001	-	-

Table 2. Path coefficients (*=*p*<0.05, **=*p*<0.01, and *=*p*<0.001).**

Indirect effects of AN on PE, of AT on UB, of EE on AT and BI, of FC on AT, BI, and UB, and of PE on BI and UB are present. Indirect effects of TT on AT, BI and UB as well as of TY on AT, BI, PE, PR, and UB could be demonstrated. The respective paths with their coefficients as well as their p-values are summarized in Table 3.

Path	Coefficient	p-Value	Path	Coefficient	p-Value
AN → PE	-0.09*	0.0424	TT → AT	0.20***	<0.001
AT → UB	0.16*	0.0120	TT → BI	0.32***	<0.001
EE → AT	0.09*	0.0277	TT → UB	0.13*	0.0206
EE → BI	0.16**	0.0041	TY → AT	0.30***	<0.001
FC → AT	0.13***	<0.001	TY → BI	0.13**	0.0067
FC → BI	0.10*	0.0135	TY → PE	0.17**	0.0017
FC → UB	0.08*	0.0231	TY → PR	-0.29***	<0.001
PE → BI	0.15**	0.0046	TY → UB	0.06*	0.0462
PE → UB	0.13***	<0.001			

Table 3. Indirect effects (*=*p*<0.05, **=*p*<0.01, and *=*p*<0.001).**

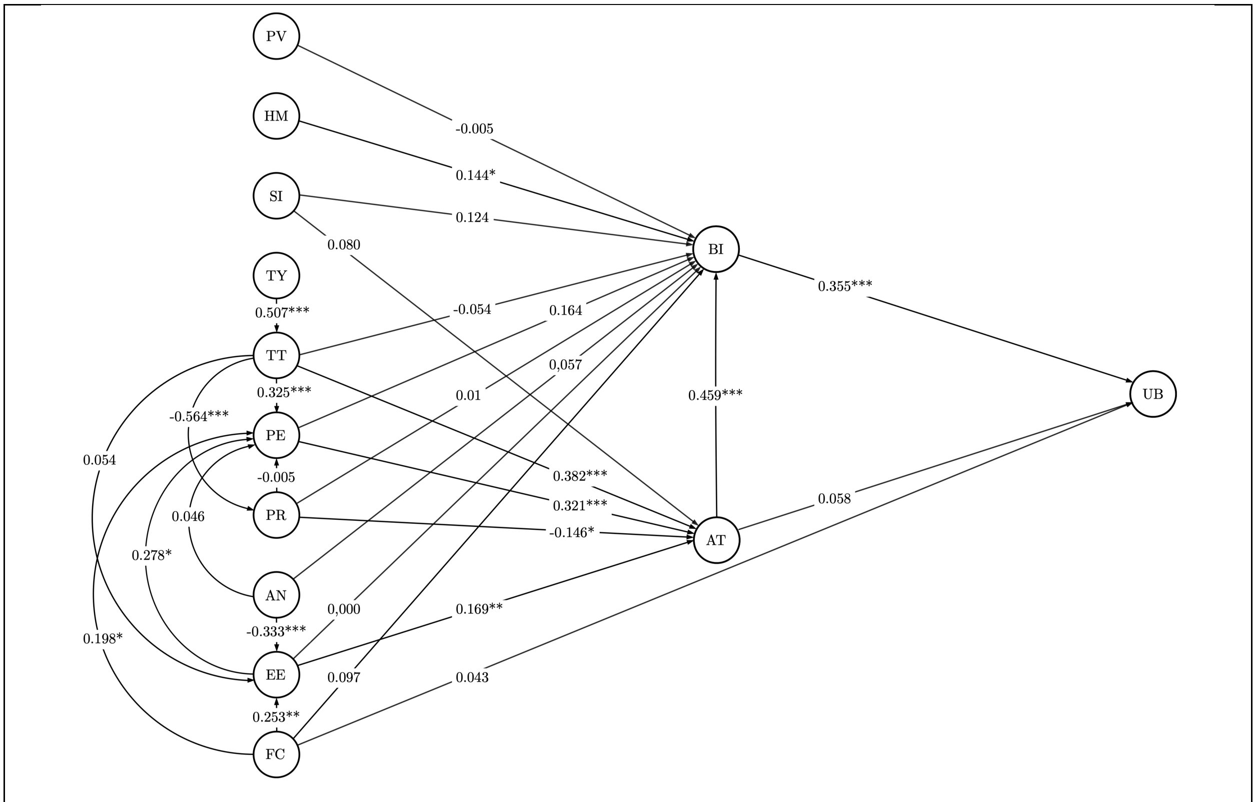

Figure 2. Path coefficients (*=*p*<0.05, **=*p*<0.01, and *=*p*<0.001).**

Discussion

We identified a direct positive effect of BI on UB (0.355***). This implies that the direct positive effect of BI on actual UB defined in UTAUT by Venkatesh et al. (2003) might be also valid in the IPA context. The comparatively strong and direct effect of AT on BI (0.459***) also suggests that the BI might be dependent on AT. In addition, the indirect effect of AT on UB (0.22*) suggests that actual usage behavior may be dependent on attitudes toward IPA in addition to BI. Dwivedi et al. (2019) were able to make comparable inferences from direct effects of AT on BI in their UTAUT meta study. The positive effect of EXP on UB (0.411***) implies that potential adopters who have EXP are more likely to use IPA than workers without prior EXP. The positive direct effect of EXP on EE (0.21*) also implies that potential adopters who have EXP perceive the use of the technology to be easier or less complex than workers without related prior knowledge. On the other hand, the direct negative effect of AN on EE (-0.333***) implies that fear of IPA or its associated technologies may have a negative impact on EE. This suggests that potential users initially perceive the complexity of use to be comparatively high due to a perception bias caused by AN, and that this effect decreases with increasing experience with the technology.

The direct effects of PE on AT (0.321***) and of EE on AT (0.169**) as well as the absence of direct effects of PE and EE on BI confirm the explanations of Dwivedi et al. (2017) that PE as well as EE initially influence the affective attitude of a potential user and not directly the intention to use the respective technology. It can be assumed that AT increases with growing PE and EE. The indirect effects of PE on BI (0.15**) and UB (0.13***) imply that BI as well as actual UB might depend on the PE of potential users. This suggests that as PE increases, BI as well as frequency of actual usage increases. The indirect effect of EE on BI (0.16*) allows analog conclusions as the effect of PE on BI. The direct effect of EE on PE (0.278*) further implies that it might be relevant in the context of IPA how high the EE of IPA is to be able to exploit the improvement and performance potentials. In this context, the PE increases with increasing EE. Analog correlations could be confirmed since the definition of TAM by Davis (1985) in different contexts (Pan et al. 2019).

The direct effects of TT on AT (0.382***) and the indirect effects of TT on BI (0.32***) and UB (0.13*) suggest that TT initially has a positive effect on AT, from there exerts positive effects on BI and UB. In addition, the direct effect of TT on PE (0.325***) allows for the conclusion that PE depends on the respective TT. It can be assumed that AT, BI, UB, and PE increase with increasing TT in the technology. Furthermore, we identified a strong negative effect of TT on PR (-0.564***). This implies that PR is reduced with increasing TT. A direct moderating effect of EXP between TT and PR (-0.160*) suggests that the effect may increase as the user's EXP increases. PR, in turn, has a direct effect on AT (-0.146**), implying that attitudes toward IPA are negatively influenced by PR. It can be assumed that the attitude to use IPA decreases with increasing perceived risk.

The positive direct effect of TY on TT (0.507***) allows the conclusion that TT in IPA is again strongly dependent on TY. This implication is consistent with the observations and assumptions of Kalimeri and Tjostheim (2020), Lipton (2018), and Wanner et al. (2022) that the explainability or transparency of models is a prerequisite for the formation of TT. Lacity et al. (2016) were able to derive comparable findings when interviewing senior executives in an RPA context. In this context, trust in the technology increases with increasing transparency of the solution. Further, we identified indirect effects of TY on AT (0.30***), BI (0.13**), PE (0.17**), UB (0.06*) as well as PR (-0.29***). These imply that the TY of IPA could have significant influence on AT, BI, PE, UB as well as PR. It can be assumed that with increasing TY, the determinants AT, BI, PE as well as UB increase and PR decreases. Wanner et al. (2021) also argued for a comprehensive relevance of TY in intelligent systems.

The direct positive effects of FC on PE (0.198*) and EE (0.253**) and the indirect positive effects of FC on AT (0.13***), BI (0.10*), and UB (0. 08*) indicate that the FC have a direct impact on the PE and EE, as well as AT and BI. It can be assumed that PE, EE, BI, AT, and UB increase with the quality of the supporting conditions. The direct effect of HM on BI (0.144*) implies that HM addressed using IPA might increase the BI. This is consistent with the observations of Suh et al. (2017) that hedonic components can be a key factor in the use of information systems. Moreover, we derived a positive total effect of SI on BI (0.16*). This could be since third parties who have already adopted the respective technology could have positive influence on potential users (Dwivedi et al. 2019). The observable positive moderating effects of JOL between PV and BI (0.15*) and PV and UB (0.05*) imply that as JOL increases, the PV of the technology is increasingly perceived positively or weighted more highly. Furthermore, the moderating effect of EXP between PV and BI (-0.15*) suggests that PV is increasingly negatively perceived by individuals with EXP. However, no significant effect was detected between PV and any other potential determinant of IPA adoption. This suggests that monetary aspects may have little or no relevance in IPA adoption. This could be due to the fact that employees usually do not have to bear the costs of used technologies themselves (Venkatesh et al. 2012).

Implications

Our research yields several theoretical and practical implications. First, we were able to confirm the high relevance of AT in technology adoption as emphasized by Dwivedi et al. (2019). Accordingly, we support the proposal to implement AT as an integral part of the UTAUT model for future acceptance research (Dwivedi et al. 2019). We can also confirm the relevance of TY and TT in the context of AI-based technologies as highlighted by Venkatesh (2022). The strong indirect and direct effects of TT and the closely related construct TY on the constructs PE, PR, AT, BI, and UB confirm the high relevance and necessity of trust research and research around explainable AI in the context of IPA. Accordingly, we propose to integrate the constructs TT and TY for acceptance research around IPA as well as related technologies as integral constructs in future research models. Second, we could not replicate or confirm any of the moderating effects included in the original UTAUT model (Venkatesh et al. 2003). While this outcome could be attributed to the sample size, the result supports Dwivedi et al. (2019) regarding the implied irrelevance of these moderators in certain contexts. The results of our research also confirms the meta studies of Williams et al. (2015) and Dwivedi et al. (2019) in the sense that for this reason the use of moderators is often omitted in technology acceptance research. Behavioral research further implies that the effect of the moderator GDR may disappear over time due to the dissolution of classic role models and stereotypes (Morris et al. 2005). Accordingly, it is suggested that a comprehensive evaluation of the meaningfulness of the proposed moderators, especially gender identity, be conducted. Third, from a practical point of view, the results imply that AT may play a central role in the adoption of IPA. Accordingly, it might be in the interest of organizations to maximize attitudes toward IPA (Dwivedi et al. 2019). Analog conclusions can be drawn from the direct effect of BI on UB, which implies that it makes sense to maximize BI. Levers potentially suitable for this purpose emerge from the following.

TT can be improved through various measures, including implementing and communicating frameworks for trustworthy AI (Thiebes et al. 2021) and developing organizational trust management. In addition, TY can be improved by the provisioning of comprehensive global and local explanations of the inner workings as well as the representation of current process flows and by implementing feedback loops that reveal the respective state of the bot and its inputs and outputs to the defined environment, as well as the intentions based on them (Holder et al. 2021). PR's negative effect could be countered by the implementation of risk management (Power 2004; 2009), including A/B testing (Deng et al. 2017), bandit services (Malekzadeh et al. 2020), and canary deployments (Tarvo et al. 2015). Robots could also have the ability to run without visual representation to ensure privacy (Syed et al. 2020). The direct effects of FC on EE and PE suggest organizations should provide tools such as training (Sabherwal et al. 2006), hands-on training (Alshare and Lane 2011), and helpdesks (Coeurderoy et al. 2014) to ensure appropriate support for initial or ongoing use of the technology. In addition, infrastructures and interfaces should be user-friendly to minimize effort (Zuiderwijk et al. 2015). Lastly, PE and AN could be improved by communicating the capabilities of IPA through documentation about the technology (Koh et al. 2010), previous achievements or use cases of automation (Lee and Song 2013), or success stories associated with IPA (Chatterjee et al. 2020; Dwivedi et al. 2017; Lacity et al. 2015). In addition, IPA projects should be actively driven by top management. It was shown that software robots are mainly adopted and widely developed and applied in organizations where top management integrates the solution into the corporate culture (Willcocks et al. 2015).

Conclusion

In our research, we identified 13 potential determinants for IPA adoption to propose an extended UTAUT model. The results indicate that, in addition to these traditional technological and organizational constructs, TT and TY can have a high impact on IPA adoption. TT and TY can significantly reduce the PR of IPA, which in turn has a negative effect on AT. TY furthermore has a strong positive effect on TT. In addition, a direct negative effect of AN on EE can be observed. AT also plays a central or mediating role between TT, PE, PR, EE, and BI. In addition, there are strong indirect effects of AT on UB. Furthermore, a moderating effect of JOL between PV and BI as well as moderating effects of EXP between TT and PR and between PV and BI could be demonstrated. There are no significant effects of PV on other model constructs. Moreover, no moderating effect of AGE or GDR could be detected. Our research contributes to theory by confirming the high relevance from AT emphasized by Dwivedi et al. (2019) as well as the relevance of black box algorithms and trust in algorithms highlighted by Venkatesh (2022) in the context of AI-based technologies. Accordingly, we propose to integrate the constructs AT, TT, and TY for acceptance research around IPA as well as related technologies as integral constructs in future research models. Our research also contributes to practice by providing actionable advice to improve IPA adoption, such as the implementation of trust management and guidelines for trustworthy AI, the dissolution of black-box models by providing explanations and observability of the software robots, comprehensive training, and education of potential users, and the implementation of design principles for maximizing ease of use as well as addressing hedonic utility aspects.

Some limitations, such as a low proportion of respondents with experience of IPA and the associated limited explanatory power of UB, the simplified, one-dimensional construction of PR, TT, and TY, the small sample size, and potential cultural biases, suggest that the proposed model may be subject to imperfections or may have more explanatory power than implied by the comparatively low explained variance of UB.

Further, the openness or restrictiveness of an organization may influence the user's attitude towards adoption and serve as an interested playing field to analyze related aspects such as workarounds to use AI and quit quitting. As a bridge towards more design-oriented research, this research can be used to inform requirements engineering and the design of complex IPA building blocks such as the aforementioned data trust models where complex and flexible interactions with multiple parties exceeds the boundaries of symbolic process automation. Lastly, future research with regard to IPA adoption must seek to develop an appropriately adjusted or extended model and/or to validate the presented model with a larger sample size. These optimizations could enable more precise inferences to be made about the determinants of IPA to increase adoption in practice.

Acknowledgements

This research and development project is funded by the German Federal Ministry of Education and Research (BMBF) within the „Richtlinie zur Förderung von Projekten zur Erforschung oder Entwicklung praxisrelevanter Lösungsaspekte („Bausteine“) für Datentreuhandmodelle“ (Funding No. 16DTM201B) and managed by VDI/VDE Innovation + Technik GmbH. The authors are responsible for the contents of this publication.

References

Ajzen, I. 1991. "The Theory of Planned Behavior," *Organizational behavior and human decision processes* (50:2), pp. 179--211.

Ajzen, I., and Fishbein, M. 1977. "Attitude-Behavior Relations: A Theoretical Analysis and Review of Empirical Research," *Psychological Bulletin* (84:5), pp. 8--918.

Alshare, K. A., and Lane, P. L. 2011. "Predicting Student-Perceived Learning Outcomes and Satisfaction in Erp Courses: An Empirical Investigation," *Communications of the association for information systems* (28:1), pp. 572--584.

Asatiani, A., and Penttinen, E. 2016. "Turning Robotic Process Automation into Commercial Success--Case Opuscapita," *Journal of Information Technology Teaching Cases* (6:2), pp. 67--74.

Azevedo, V., Carvalho, M., Fernandes-Costa, F., Mesquita, S., Soares, J., Teixeira, F., and Maia, n. 2017. "Interview Transcription: Conceptual Issues, Practical Guidelines, and Challenges," *Revista de Enfermagem Referencia* (4:14), pp. 159--167.

Bandura, A. 1986. "Social Foundations of Thought and Action," *Englewood Cliffs, NJ* (1986:23-28).

Boone, H. N., and Boone, D. A. 2012. "Analyzing Likert Data," *Journal of extension* (50:2), pp. 1--5.

Cambre, M. A., and Cook, D. L. 1985. "Computer Anxiety: Definition, Measurement, and Correlates," *Journal of Educational Computing Research* (1:1), pp. 37--54.

Chakraborti, T., Isahagian, V., Khalaf, R., Khazaeni, Y., Muthusamy, V., Rizk, Y., and Unuvar, M. 2020. "From Robotic Process Automation to Intelligent Process Automation," in: *International Conference on Business Process Management*. Cham: Springer, pp. 215--228.

Chatterjee, S., Nguyen, B., Ghosh, S. K., Bhattacharjee, K. K., and Chaudhuri, S. 2020. "Adoption of Artificial Intelligence Integrated Crm System: An Empirical Study of Indian Organizations," *The Bottom Line*), pp. 359--375.

Chin, W. W. 1998. "The Partial Least Squares Approach to Structural Equation Modeling," *Modern methods for business research* (295:2), pp. 295-336.

Choi, J. K., and Ji, Y. G. 2015. "Investigating the Importance of Trust on Adopting an Autonomous Vehicle," *International Journal of Human-Computer Interaction* (31:10), pp. 692--702.

Coeurderoy, R., Guilmot, N., and Vas, A. 2014. "Explaining Factors Affecting Technological Change Adoption: A Survival Analysis of an Information System Implementation," *Management Decision* (52:6), pp. 1085--1100.

Compeau, D. R., and Higgins, C. A. 1995. "Application of Social Cognitive Theory to Training for Computer Skills," *Information systems research* (6:2), pp. 118--143.

Crockett, K., Garratt, M., Latham, A., Colyer, E., and Goltz, S. 2020. "Risk and Trust Perceptions of the Public of Artifical Intelligence Applications," in: *2020 International Joint Conference on Neural Networks (IJCNN)*. IEEE, pp. 1--8.

Cunningham, L. F., Gerlach, J. H., Harper, M. D., and Young, C. E. 2005. "Perceived Risk and the Consumer Buying Process: Internet Airline Reservations," *International Journal of Service Industry Management*), pp. 357--372.

Dam, H. K., Tran, T., and Ghose, A. 2018. "Explainable Software Analytics," in: *Proceedings of the 40th International Conference on Software Engineering*. pp. 53--56.

Danckwerts, S., Meiner, L., and Krampe, C. 2020. "Hi, Can You Recommend a Movie?” Investigating Recommendation Chatbots in Media Streaming Services," in: *ECIS 2020-28th European Conference on Information Systems. Liberty, Equality and Fraternity In a Digitizing World*. pp. 1--13.

Davis, F. D. 1985. "A Technology Acceptance Model for Empirically Testing New End-User Information Systems: Theory and Results." Massachusetts Institute of Technology, pp. 1-291.

Davis, F. D. 1989. "Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology," *MIS quarterly* (13:3), pp. 319--340.

Davis, F. D., Bagozzi, R. P., and Warshaw, P. R. 1992. "Extrinsic and Intrinsic Motivation to Use Computers in the Workplace 1," *Journal of applied social psychology* (22:14), pp. 1111--1132.

Deng, A., Dmitriev, P., Gupta, S., Kohavi, R., Raff, P., and Vermeer, L. 2017. "A/B Testing at Scale: Accelerating Software Innovation," in: *Proceedings of the 40th International ACM SIGIR Conference on Research and Development in Information Retrieval*. pp. 1395--1397.

Devi, S., Kumar, S., and Kushwaha, G. S. 2016. "An Adaptive Neuro Fuzzy Inference System for Prediction of Anxiety of Students," in: *2016 eighth international conference on advanced computational intelligence (ICACI)*. IEEE, pp. 7--13.

Dodds, W. B., Monroe, K. B., and Grewal, D. 1991. "Effects of Price, Brand, and Store Information on Buyers' Product Evaluations," *Journal of marketing research* (28:3), pp. 307--319.

Dohmen, T. J., Kriechel, B., and Pfann, G. A. 2004. "Monkey Bars and Ladders: The Importance of Lateral and Vertical Job Mobility in Internal Labor Market Careers," *Journal of Population Economics* (17:2), pp. 193--228.

Dumas, M., La Rosa, M., Mendling, J., and Reijers, H. A. 2018. *Fundamentals of Business Process Management*. Heidelberg: Springer.

Dwivedi, Y. K., Rana, N. P., Janssen, M., Lal, B., Williams, M. D., and Clement, M. 2017. "An Empirical Validation of a Unified Model of Electronic Government Adoption (Umega)," *Government Information Quarterly* (34:2), pp. 211--230.

Dwivedi, Y. K., Rana, N. P., Jeyaraj, A., Clement, M., and Williams, M. D. 2019. "Re-Examining the Unified Theory of Acceptance and Use of Technology (Utaut): Towards a Revised Theoretical Model," *Information Systems Frontiers* (21:3), pp. 719--734.

Eisser, J., Torrini, M., and Bhm, S. 2020. "Automation Anxiety as a Barrier to Workplace Automation: An Empirical Analysis of the Example of Recruiting Chatbots in Germany," in: *Proceedings of the 2020 on Computers and People Research Conference*. pp. 47--51.

Engel, C., Ebel, P., and Leimeister, J. M. 2022. "Cognitive Automation," *Electronic Markets* (32:1), pp. 339-350.

Featherman, M. S., and Pavlou, P. A. 2003. "Predicting E-Services Adoption: A Perceived Risk Facets Perspective," *International journal of human-computer studies* (59:4), pp. 451--474.

Fersht, P., and Slaby, J. R. 2012. "Robotic Automation Emerges as a Threat to Traditional Low-Cost Outsourcing," *HfS Research. Retrieved August* (16), pp. 1--19.

Gartner. 2019. "Top 10 Strategic Technology Trends for 2020." from https://www.gartner.com/smarterwithgartner/gartner-top-10-strategic-technology-trends-for-2020

Grashof, N., and Kopka, A. 2022. "Artificial Intelligence and Radical Innovation: An Opportunity for All Companies?," *Small Business Economics*), pp. 1-27.

Hair, J. F., Hult, G. T. M., Ringle, C. M., and Sarstedt, M. 2014. *A Primer on Partial Least Squares Structural Equation Modeling*. Taylor & Francis.

Hair, J. F., Ringle, C. M., and Sarstedt, M. 2011. "Pls-Sem: Indeed a Silver Bullet," *Journal of Marketing theory and Practice* (19:2), pp. 139--152.

Hair, J. F., Risher, J. J., Sarstedt, M., and Ringle, C. M. 2019a. "When to Use and How to Report the Results of Pls-Sem," *European Business Review* (31:1), pp. 2--24.

Hair, J. F., Sarstedt, M., and Ringle, C. M. 2019b. "Rethinking Some of the Rethinking of Partial Least Squares," *European Journal of Marketing* (53:4), pp. 1--19.

Harber, D., Marriott, F., and Idrus, N. 1991. "Employee Participation in Tqc: The Effect of Job Levels on Participation and Job Satisfaction," *International Journal of Quality & Reliability Management*), pp. 35--54.

Henseler, J., Ringle, C. M., and Sarstedt, M. 2015. "A New Criterion for Assessing Discriminant Validity in Variance-Based Structural Equation Modeling," *Journal of the academy of marketing science* (43:1), pp. 115--135.

Herm, L.-V., Janiesch, C., Reijers, H. A., and Seubert, F. 2021. "From Symbolic Rpa to Intelligent Rpa: Challenges for Developing and Operating Intelligent Software Robots," in: *International Conference on Business Process Management*. Cham: Springer, pp. 289--305.

Herm, L.-V., Wanner, J., and Janiesch, C. 2022. "A Taxonomy of User-Centered Explainable Ai Studies," in: *PACIS 2022 Proceedings 9*. Taipei-Sydney: pp. 1-17.

Holder, E., Huang, L., Chiou, E., Jeon, M., and Lyons, J. B. 2021. "Designing for Bi-Directional Transparency in Human-Ai-Robot-Teaming," *Human Factors and Ergonomics Society Annual Meeting*, pp. 57--61.

Hsu, C.-L., Chen, M.-C., Lin, Y.-H., Chang, K.-C., and Hsieh, A.-Y. 2014. "Adopting the Extension of Utaut Model to Investigate the Determinants of E-Book Adoption," in: *International Conference on Information Science, Electronics and Electrical Engineering*. pp. 669--673.

IEEE. 2017. "Ieee Guide for Terms and Concepts in Intelligent Process Automation," *IEEE Std 2755-2017*), pp. 1-16.

Jacoby, J., and Kaplan, L. B. 1972. "The Components of Perceived Risk," in: *Proceedings of the Third Annual Conference of the Association for Consumer Research*. pp. 382--393.

Janiesch, C., Zschech, P., and Heinrich, K. 2021. "Machine Learning and Deep Learning," *Electronic Markets* (31:3), pp. 685-695.

Jianbin, S., and Jiaojiao, L. 2013. "An Empirical Study of User Acceptance on Medical and Health Website Based on Utaut," *WHICEB 2013 Proceedings* (81), pp. 490--497.

Jin, G. Z., and et al. 2018. "Artificial Intelligence and Consumer Privacy," *The Economics of Artificial Intelligence: An Agenda; Agrawal, A., Gans, J., Goldfarb, A., Eds*), pp. 439--462.

Jyoti, R., and Szurley, M. 2021. "The Business Value of Ibm Ai-Powered Automation Solutions." from http://web.archive.org/web/20220420034534/https://www.ibm.com/downloads/cas/LBNMV4RO

Kalimeri, K., and Tjostheim, I. 2020. "Artificial Intelligence and Concerns About the Future: A Case Study in Norway." pp. 273--284.

Kaplan, L. B., Szybillo, G. J., and Jacoby, J. 1974. "Components of Perceived Risk in Product Purchase: A Cross-Validation.," *Journal of applied Psychology* (59:3), pp. 287--291.

Kim, K. J., and Shin, D.-H. 2015. "An Acceptance Model for Smart Watches: Implications for the Adoption of Future Wearable Technology," *Internet Research* (25:4), pp. 527--541.

Kim, S. S., Malhotra, N. K., and Narasimhan, S. 2005. "Research Note—Two Competing Perspectives on Automatic Use: A Theoretical and Empirical Comparison," *Information systems research* (16:4), pp. 418--432.

Kock, N., and Hadaya, P. 2018. "Minimum Sample Size Estimation in Pls-Sem: The Inverse Square Root and Gamma-Exponential Methods," *Information systems journal* (28:1), pp. 227--261.

Koh, C. E., Prybutok, V. R., Ryan, S. D., and et al. 2010. "A Model for Mandatory Use of Software Technologies: An Integrative Approach by Applying Multiple Levels of Abstraction of Informing Science," *Informing Science* (13), p. 177.

Lacity, M., Willcocks, L. P., and Craig, A. 2015. "Robotic Process Automation: Mature Capabilities in the Energy Sector,"), pp. 1--19.

Lacity, M., Willcocks, L. P., and Craig, A. 2016. "Robotizing Global Financial Shared Services at Royal Dsm," *The outsourcing unit working research paper series*), pp. 1--26.

Lee, J.-H., and Song, C.-H. 2013. "Effects of Trust and Perceived Risk on User Acceptance of a New Technology Service," *Social Behavior and Personality: an international journal* (41:4), pp. 587--597.

Lee, M.-C. 2009. "Factors Influencing the Adoption of Internet Banking: An Integration of Tam and Tpb with Perceived Risk and Perceived Benefit," *Electronic commerce research and applications* (8:3), pp. 130--141.

Li, M., and Suh, A. 2021. "Machinelike or Humanlike? A Literature Review of Anthropomorphism in Ai-Enabled Technology," in: *Proceedings of the 54th Hawaii International Conference on System Sciences*. pp. 4053-4062.

Lipton, Z. C. 2018. "The Mythos of Model Interpretability: In Machine Learning, the Concept of Interpretability Is Both Important and Slippery.," *Queue* (16:3), pp. 31--57.

Malekzadeh, M., Athanasakis, D., Haddadi, H., and Livshits, B. 2020. "Privacy-Preserving Bandits," *Proceedings of Machine Learning and Systems* (2), pp. 350--362.

Marko, S., Joseph, F. H., Christian, M. R., Kai, O. T., and Siegfried, P. G. 2016. "Estimation Issues with Pls and Cbsem: Where the Bias Lies!," *Journal of Business Research* (69:10), pp. 3998-4010.

Maurer, M. M., and Simonson, M. R. 1984. "Development and Validation of a Measure of Computer Anxiety.," in: *Annual Meeting of the Association for Educational Communications and Technology*.

Mayr, A., Stahmann, P., Nebel, M., and Janiesch, C. 2023. "Appendix for Unified Theory of Acceptance and Use of Technology (Utaut) for Intelligent Process Automation." from https://doi.org/10.23728/b2share.644c3ed380534ef18aaf0607fd423362.

McKnight, D. H., Carter, M., Thatcher, J. B., and Clay, P. F. 2011. "Trust in a Specific Technology: An Investigation of Its Components and Measures," *ACM Transactions on management information systems (TMIS)* (2:2), pp. 1--25.

McKnight, D. H., and Chervany, N. L. 2001. "Trust and Distrust Definitions: One Bite at a Time," in *Trust in Cyber-Societies*. pp. 27--54.

McKnight, D. H., Choudhury, V., and Kacmar, C. 2002. "Developing and Validating Trust Measures for E-Commerce: An Integrative Typology," *Information systems research* (13:3), pp. 334--359.

Mesbah, N., Tauchert, C., Olt, C. M., and Buxmann, P. 2019. "Promoting Trust in Ai-Based Expert Systems," *AMCIS 2019 Proceedings* (6), pp. 1-10.

Moore, G. C., and Benbasat, I. 1991. "Development of an Instrument to Measure the Perceptions of Adopting an Information Technology Innovation," *Information systems research* (2:3), pp. 192--222.

Moore, G. C., and Benbasat, I. 1996. "Integrating Diffusion of Innovations and Theory of Reasoned Action Models to Predict Utilization of Information Technology by End-Users," in *Diffusion and Adoption of Information Technology*. pp. 132--146.

Morris, M. G., Venkatesh, V., and Ackerman, P. L. 2005. "Gender and Age Differences in Employee Decisions About New Technology: An Extension to the Theory of Planned Behavior," *IEEE transactions on engineering management* (52:1), pp. 69--84.

Pan, J., Ding, S., Wu, D., Yang, S., and Yang, J. 2019. "Exploring Behavioural Intentions toward Smart Healthcare Services among Medical Practitioners: A Technology Transfer Perspective," *International Journal of Production Research* (57:18), pp. 5801--5820.

Pei, W., Mayer, A., Tu, K., and Yue, C. 2020. "Attention Please: Your Attention Check Questions in Survey Studies Can Be Automatically Answered," *The Web Conference 2020*, pp. 1182--1193.

Power, M. 2004. "The Risk Management of Everything," *The Journal of Risk Finance* (5:3), pp. 58--65.

Power, M. 2009. "The Risk Management of Nothing," *Accounting, organizations and society* (34:6-7), pp. 849--855.

Qiu, L., and Benbasat, I. 2009. "Evaluating Anthropomorphic Product Recommendation Agents: A Social Relationship Perspective to Designing Information Systems," *Journal of management information systems* (25:4), pp. 145--182.

Ringle, C. M., Wende, S., Becker, J.-M., and et al. 2015. "Smartpls 3," *Boenningstedt: SmartPLS GmbH* (584).

Rohner, D. J., and Simonson, M. R. 1981. "Development of an Index of Computer Anxiety," *Research and Theory Division of the Association for Educational Communications and Technology*, pp. 549-585.

Sabherwal, R., Jeyaraj, A., and Chowa, C. 2006. "Information System Success: Individual and Organizational Determinants," *Management science* (52:12), pp. 1849--1864.

Sheppard, B. H., Hartwick, J., and Warshaw, P. R. 1988. "The Theory of Reasoned Action: A Meta-Analysis of Past Research with Recommendations for Modifications and Future Research," *Journal of consumer research* (15:3), pp. 325--343.

Shin, D. 2021. "The Effects of Explainability and Causability on Perception, Trust, and Acceptance: Implications for Explainable Ai," *International Journal of Human-Computer Studies* (146:102551), pp. 1--10.

Stone, R. N., and Grønhaug, K. 1993. "Perceived Risk: Further Considerations for the Marketing Discipline," *European Journal of marketing* (27:3), pp. 39--50.

Suh, A., Cheung, C. M. K., Ahuja, M., and Wagner, C. 2017. "Gamification in the Workplace: The Central Role of the Aesthetic Experience," *Journal of Management Information Systems* (34:1), pp. 268--305.

Syed, R., Suriadi, S., Adams, M., Bandara, W., Leemans, S. J. J., Ouyang, C., ter Hofstede, A. H. M., van de Weerd, I., Wynn, M. T., and Reijers, H. A. 2020. "Robotic Process Automation: Contemporary Themes and Challenges," *Computers in Industry* (115), p. 103162.

Tarvo, A., Sweeney, P. F., Mitchell, N., Rajan, V. T., Arnold, M., and Baldini, I. 2015. "Canaryadvisor: A Statistical-Based Tool for Canary Testing," *2015 International Symposium on Software Testing and Analysis*, pp. 418--422.

Taylor, S., and Todd, P. 1995. "Assessing It Usage: The Role of Prior Experience," *MIS quarterly* (19:4), pp. 561--570.

Thiebes, S., Lins, S., and Sunyaev, A. 2021. "Trustworthy Artificial Intelligence," *Electronic Markets* (31:2), pp. 447--464.

Thompson, R. L., Higgins, C. A., and Howell, J. M. 1991. "Personal Computing: Toward a Conceptual Model of Utilization," *MIS quarterly* (15:1), pp. 125--143.

Thong, J. Y. L., Hong, S.-J., and Tam, K. Y. 2006. "The Effects of Post-Adoption Beliefs on the Expectation-Confirmation Model for Information Technology Continuance," *International Journal of human-computer studies* (64:9), pp. 799--810.

Triandis, H. C. 1977. *Interpersonal Behavior*. Brooks/Cole Publishing Company.

Tripp, J., McKnight, D. H., and Lankton, N. K. 2011. "Degrees of Humanness in Technology: What Type of Trust Matters?," *AMCIS 2011 Proceedings - All Submissions* (149), pp. 1--9.

Vallerand, R. J. 1997. "Toward a Hierarchical Model of Intrinsic and Extrinsic Motivation," *Advances in experimental social psychology* (29), pp. 271--360.

van der Aalst, W. M. P., Bichler, M., and Heinzl, A. 2018. "Robotic Process Automation," *Business \& Information Systems Engineering: The International Journal of Wirtschaftsinformatik* (60:4), pp. 269--272.

van der Heijden, H. 2004. "User Acceptance of Hedonic Information Systems," *MIS quarterly* (28:4), pp. 695--704.

Venkatesh, V. 2022. "Adoption and Use of Ai Tools: A Research Agenda Grounded in Utaut," *Annals of Operations Research* (308:1), pp. 641-652.

Venkatesh, V., and Bala, H. 2008. "Technology Acceptance Model 3 and a Research Agenda on Interventions," *Decision sciences* (39:2), pp. 273--315.

Venkatesh, V., Morris, M. G., Davis, G. B., and Davis, F. D. 2003. "User Acceptance of Information Technology: Toward a Unified View," *MIS quarterly* (27:3), pp. 425--478.

Venkatesh, V., and Speier, C. 1999. "Computer Technology Training in the Workplace: A Longitudinal Investigation of the Effect of Mood," *Organizational behavior and human decision processes* (79:1), pp. 1--28.

Venkatesh, V., Thong, J. Y. L., and Xu, X. 2012. "Consumer Acceptance and Use of Information Technology: Extending the Unified Theory of Acceptance and Use of Technology," *MIS quarterly* (36:1), pp. 157--178.

vom Brocke, J., Simons, A., Riemer, K., Niehaves, B., Plattfaut, R., and Cleven, A. 2015. "Standing on the Shoulders of Giants: Challenges and Recommendations of Literature Search in Information Systems Research," *Communications of the association for information systems* (37:1), p. 9.

Voorhees, C. M., Brady, M. K., Calantone, R., and Ramirez, E. 2016. "Discriminant Validity Testing in Marketing: An Analysis, Causes for Concern, and Proposed Remedies," *Journal of the academy of marketing science* (44:1), pp. 119--134.

Wanner, J., Herm, L.-V., Heinrich, K., and Janiesch, C. 2022. "The Effect of Transparency and Trust on Intelligent System Acceptance: Evidence from a User-Based Study," *Electronic Markets* (32), pp. 2079–2102

Wanner, J., Popp, L., Fuchs, K., Heinrich, K., Herm, L.-V., and Janiesch, C. 2021. "Adoption Barriers of Ai: A Context-Specific Acceptance Model for Industrial Maintenance," in: *Twenty-Ninth European Conference on Information Systems* pp. 1--13.

Webster, J., and Watson, R. T. 2002. "Analyzing the Past to Prepare for the Future: Writing a Literature Review," *MIS quarterly* (26:2), pp. xiii--xxiii.

Willaby, H. W., Costa, D. S. J., Burns, B. D., MacCann, C., and Roberts, R. D. 2015. "Testing Complex Models with Small Sample Sizes: A Historical Overview and Empirical Demonstration of What Partial Least Squares (Pls) Can Offer Differential Psychology," *Personality and Individual Differences* (84), pp. 73--78.

Willcocks, L. P., Lacity, M., and Craig, A. 2015. "Robotic Process Automation at Xchanging," London School of Economics and Political Science, LSE Library, pp. 1--26.

Williams, M. D., Rana, N. P., and Dwivedi, Y. K. 2015. "The Unified Theory of Acceptance and Use of Technology (Utaut): A Literature Review," *Journal of enterprise information management* (28:3), pp. 443--488.

Zuiderwijk, A., Janssen, M., and Dwivedi, Y. K. 2015. "Acceptance and Use Predictors of Open Data Technologies: Drawing Upon the Unified Theory of Acceptance and Use of Technology," *Government information quarterly* (32:4), pp. 429--440.