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RESEARCH PAPER

Still doing it yourself? Investigating determinants for the adoption of intelligent process automation

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Abstract

Intelligent process automation (IPA) augments symbolic process automation using artificial intelligence. Emulating human decision-making, IPA enables the execution of complex processes requiring decision-making capacities. IPA promises great economic potential as it enables more efficient use of the human workforce. However, the adoption rate in practice falls behind these potentials. Our study aims to investigate reasons and identify areas for action towards IPA adoption. To this end, we identified 13 determinants and created an extended UTAUT model. We tested the model with partial least squares structural equation modeling for significant influential relationships between the determinants based on a user study. We contribute to theory and practice finding a special role of trust and transparency for the adoption of IPA. Likewise, we show that organizations should cultivate a positive attitude towards IPA diffusion. Further, our results contribute with a focus on the potential adopters as IPA adoption is contingent upon their characteristics, such as experience and job level.

Keywords Intelligent process automation · Business process management · Robotic process automation · UTAUT · Technology adoption

JEL Classification C9 · M15

Introduction

The idea of automation has characterized efficient work design for decades. Along with technological advancements, tasks originally performed by humans have been delegated to new technology (Rinta-Kahila et al., 2023). For example, machines have been designed to automate repetitive manufacturing tasks or office work. Delegation to technology has leveraged two kinds of advantages. On the one hand, workers' capacities that were invested in repetitive tasks could be used otherwise. On the other hand, automation streamlined task execution leading to reductions in operational failures and manufacturing variations. Opposed to physical labor, knowledge-intensive tasks have remained mostly untouched by automation as they required human cognition for decision-making (Rinta-Kahila et al., 2023). However, the pressure to automate knowledge-intensive tasks grows as the work amount in front and back offices increases every year binding more and more capacity (Willcocks, 2020).

To leverage back office and front office automation potentials in the past, organizations have used symbolic process automation enabled by business process management

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A prior version of this research has been published here: https://aisel.aisnet.org/icis2023/itadopt/itadopt/6/. We significantly extended the prior publication throughout all sections, but especially in the methodology, result presentation, and discussion. The authors have the legal rights for further publications.

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(BPM) systems and robotic process automation (RPA) software (Herm et al., 2021) to automate highly standardized and transaction-intensive processes (Asatiani & Penttinen, 2016; Fersht & Slaby, 2012). As symbolic process automation necessitates the explicit formulation of sequence flows and rules, it cannot be used for a significant portion of business processes that require cognitive efforts, such as complex decision-making or judgment (Chakraborti et al., 2020).

Intelligent (process) automation (IPA) complements symbolic process automation with artificial intelligence (AI) technology, which mimics human cognitive abilities for decision-making (Engel et al., 2023; 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 until recently. IPA 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 increases 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 & 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 & Bala, 2008). This raises the question which factors determine successful embedding of IPA in organizations (Engel et al., 2022) and, hence, adoption by employees. To investigate the determinants and further identify implications that are likely to increase the adoption rate of IPA, we formulate the following research question:

RQ: *Which determinants influence the adoption of intelligent process automation by employees?*

Providing answers to this research question, we respond to the call for research by Engel et al. (2022), who observe a low adoption rate of IPA in business organization despite their awareness of its great potentials. Specifically, the call addresses leveraging work system-oriented research opportunities regarding a socio-technical understanding of how to embed IPA in organizations. With our research, we identified determinants for IPA adoption from literature and practice and extended the established Unified Theory of Acceptance and Use of Technology (UTAUT) model accordingly. Our contribution focuses an extension of the established UTAUT model specifically for IPA adoption. We evaluated the extended model in an iterative manner. Our results show that in addition to established factors for technology adoption, trust, transparency, and attitude towards technology are primary decision factors. Therefore, we argue for the cultivation of a positive attitude towards IPA and the establishment of facilitating conditions for its use. In a similar vein, based on our study results, we emphasize the influence of user experience as well as trust facilitated by transparency on IPA adoption.

The remainder of this paper is structured as follows: "Theoretical background" outlines the theoretical background on process automation and the adoption of IPA. "Research design" covers the research design. Subsequently, "Derivation of determinants and hypotheses" details the derivation of potential determinants for adoption. "Model evaluation" presents the evaluation of the model, "Hypothesis evaluation" the evaluation of the hypotheses. "Discussion" includes a discussion, implications for theory and practice, and limitations. Lastly, in "Conclusion and future work," we draw a conclusion and provide starting points for future research.

Theoretical background

Symbolic and intelligent automation of processes

(Knowledge) Work is usually organized in interrelated processes comprising events, tasks, and decision points. Involved actors interact with physical or intangible objects to pursue business goals typically comprising quantifiable value. Using traditional process automation means such as business process management (BPM) systems or robotic process automation (RPA), the sequence of the tasks is determined by handcrafted process models. Decision gateways enable variants in execution (Dumas et al., 2018).

Processes can be differentiated by many means. One example is frequency and variance of tasks (van der Aalst et al., 2018). Traditionally, processes that are of high frequency and only exhibit reasonable variance are automated by heavyweight BPM systems as workflows. These implementations rely on handcrafted process models, interfaces to BPM software and often involve multiple departments within or across companies. Processes that involve highly repetitive tasks but do not have a frequency and feasibility high enough for heavyweight automation are—of recently—candidates for lightweight automation with RPA. RPA is a generic term that summarizes a large number of different automation approaches. They have the common characteristic of performing digital, yet manual activities without changing existing software by instantiating software robots as agents that imitate human users instead (van der Aalst et al., 2018). These software robots act on the user interface (UI) and do not intervene into application code (Agostinelli et al., 2019) as suitable interfaces other than the UI often do not exist. RPA use intends to remove labor-intensive, repetitive tasks from the workload of human workers (Chakraborti

et al., 2020). Processes that are typically prone to automation with RPA are characterized by 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 & Penttinen, 2016; Fersht & Slaby, 2012). Moving, pasting, copying, unpacking, and merging data between systems are typical examples (Aguirre & Rodriguez, 2017). As with BPM systems, RPA requires implementation in a symbolic manner by formulating explicit sequence flows and decision rules (Asatiani & Penttinen, 2016; Fersht & Slaby, 2012). Both approaches can be summarized under the term *symbolic process automation* (Herm et al., 2021).

However, a significant portion of business processes cannot be automated in this manner as they require cognitive capacities (Chakraborti et al., 2020). IPA subsumes approaches that potentially overcome the limitations of symbolic process automation (Engel et al., 2022). IPA represents an approach that complements and augments the methods of symbolic process automation with the benefits of AI.

Enhancing process automation with AI based on machine learning entails a significant shift from deterministic rule-based to probabilistic learning-based logic (Engel et al., 2023). As machine learning leverages various kinds of statistical methods and is used for a variety of purposes, there are multiple facets to its definition (Russell & Norvig, 2021). Regarding process automation, AI based on machine learning contributes with capabilities of autonomous, self-adapting decision-making behavior (Engel et al., 2022). AI decision-making is inspired by biological cognition as AI attempts to emulate human intelligence (Janiesch et al., 2021). Combined with advancements in computing power, AI constitutes a strong accelerator for process automation as it comprises complex probabilistic models enabling reflected, adapting decision-making (Dalzochio et al., 2020). IPA therefore holds potential to automate complex processes and tasks that otherwise must be completed by humans. Processes that can potentially benefit from these abilities typically comprise a large number of decision variables, from simple tasks such as invoice verification to complex tasks such as enabling sharing data within data trust models. More generally, IPA bears potential for tasks covering evaluations, reasoning, decision-making, and process fulfillment of deterministic and probabilistic nature (Chakraborti et al., 2020; IEEE, 2017). Therefore, IPA can significantly contribute to strategic business transformation by leveraging operational efficiency (Lacity et al., 2021).

Adoption of intelligent process automation and theories of acceptance and use

Despite the potential to gain a competitive edge, companies are hesitant when it comes to IPA adoption. Reports on realizing advantages due to IPA have prognostic character, but do not reflect operational practice (Lacity et al., 2018). Only about one quarter of early technology adopters have implemented IPA (Lacity et al., 2021). Hesitation is due to a variety of risks that specifically affect knowledge workers on operational level. Exemplary risks are disclosed advantages, lack of communication, estimated complexity of IPA adoption, insufficient change management, and fear of being replaced by technology (Engel et al., 2023). However, literature on determinants for IPA adoption is scarce, while calling for more actionable research on IPA adoption prevail (Engel et al., 2022; e.g., Engel et al., 2023).

When it comes to the adoption of novel technology, Information Systems research typically draws on established models to investigate adoption determinants and their relationships. UTAUT models are primarily evaluated in research using structural equation modeling (SEM) (Williams et al., 2015). Structural equation modeling (SEM) aims to depict theoretically or logically founded relationships between latent constructs in a system of equations. The method can be used to estimate dependencies and errors between the defined constructs (Weiber & Mühlhaus, 2014). The suitability of UTAUT was proven in different contexts of technology acceptance (Hsu et al., 2014). For example, over 70 percent of the variance of the corresponding target variables could be explained in a large number of studies (Sohn & Kwon, 2020).

Besides UTAUT, further theories exist that cater for similar yet slightly different contexts. The *Technology Acceptance Model* (TAM) aims at understanding acceptance and adoption of new technologies (Venkatesh & Bala, 2008). Additional to behavioral intention and use behavior, perceived usefulness and perceived ease of use are the constructs at its core, which are altered by various determinants such as social influence. Furthermore, the *Theory of Planned Behavior* conceptualizes a user's intention of performing a behavior with an information system as determined by their attitude, subjective norms as well as perceived behavioral control (Ajzen, 1991). The *Social Cognitive Theory* targets fostering an understanding of how observation, imitation, and reinforcement in social environments influence cognitive processes during technology adoption (D. Compeau et al., 1999). Comparably, the *Theory of Reasoned Action* considers users' behavioral intention the key determinant of their actual behavior (Sheppard et al., 1988). While the original theory does not explicitly refer to technology adoption, insights, for example on the role of subjective norms, have been used in Information Systems research in this regard (e.g., Albayati et al., 2020; Jain et al., 2022). Moreover, the *Motivational Model* sets apart by scrutinizing individual intrinsic and motivators which lead to different levels of technology engagement (Vallerand, 1997). The individual motivational model of users is conceptualized to be a major

determinant of technology adoption. In addition, the *Innovation Diffusion Theory* characterizes a process for the adoption of new technologies by users (Moore & Benbasat, 1991). In this regard, technology adoption follows a predictable pattern differentiating, for example, innovative users adopting new technologies from more traditional laggards.

Pursuing our research goal, we decided to use an established model, either UTAUT or TAM. This allows us to stand on the shoulders of those who introduced and evaluated the original as well as further variables and items in this context. This enables the comparison of our results with prior and future research and allows us to draw broader conclusions taking into consideration the results of others as well. Developing our own model would have increased the complexity of our investigation and would have made this comparability of results more difficult. The risk of establishing YAMA, yet another modeling approach, is something we strived to avoid (Oei et al., 1992). Aligning with Venkatesh (2022), who explicitly proposed the use of UTAUT to investigate acceptance of AI-related technology, we decided for UTAUT. Furthermore, UTAUT is often extended in literature to include specific constructs to customize to specific adoption contexts (Chatterjee & Bhattacharjee, 2020; Venkatesh, 2022; Williams et al., 2015). As exemplary extension, Venkatesh et al. (2012) developed UTAUT2 confirming the structure of UTAUT, but additionally covering Hedonic Motivation and Price Value.

In addition, we argue that business processes may constitute a complex field for automation (e.g., Engel et al., 2022). To grasp the complexity from an acceptance perspective, we selected UTAUT due to the variety of considered constructs originating from a variety of established technology acceptance models (Ajzen, 1991; Bandura, 1986; D. R. Compeau & Higgins, 1995; Davis, 1985; cf. Davis, 1989; Davis et al., 1989, 1992; Moore & Benbasat, 1991, 1996; Sheppard et al., 1988; Taylor & Todd, 1995; Thompson et al., 1991; Triandis, 1977; Vallerand, 1997; Venkatesh et al., 2003; Venkatesh & Speier, 1999). This foundation is critical to understanding technology acceptance in the focused organizational setting. As we are among the first ones with our focus of investigation, we wanted to incorporate a comprehensive spectrum of meaningful to get a broad understanding of acceptance of IPA.

Research design

The goal of our research is to identify determinants for IPA adoption. Using the determinants, we aim for an extension of the UTAUT model that contributes to the research domains of technology acceptance and process automation. Figure 1 shows the methodologies we used and how we related them in correspondence to related research (cf. Sumak et al., 2010; Wanner et al., 2022).

The methodological procedure comprises six steps as outlined in the following. The steps either focus on theory building or evaluation.

(a) To understand the theoretical basis and for the initial identification of determinants for IPA adoption, we conducted a structured literature review (vom Brocke et al., 2009; vom Brocke et al., 2015). We used the five databases ACM Digital Library, AISeL, EBSCOhost Business Source Premier, IEEEXplore, and Web of Science. The choice of databases was due to their coverage of high-quality outlets of related research from Information Systems. We used the search term ((“unified theory of acceptance and use of technology” OR utaut OR “technology acceptance model” OR “theory of planned behavior” OR “social cognitive theory” OR “theory of reasoned action” OR “motivational model” OR “Innovation diffusion theory”) AND (“business

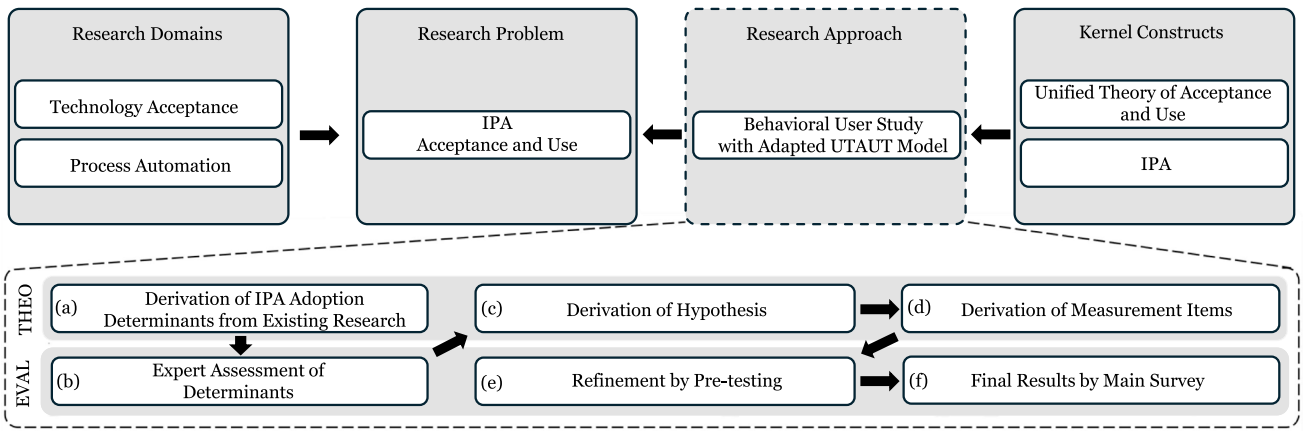


Fig. 1 Research procedure

process management" OR "intelligent automation" OR "process automation" OR "artificial intelligence")). The first part of the search term refers to UTAUT as well as related theories comprising potential determinants relevant for extending UTAUT. The second part of the search term broadly covers terms relating to the (intelligent) automation of business processes. We considered scientific journals and conference proceedings. Initially, we identified 2441 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. During scanning and full text analysis we excluded all publications that (1) did not refer to the intelligent automation of processes or (2) did not contribute to the identification of adoption determinants, for example, as they were purely theoretical. Publications covering models on technology acceptance were omitted from the first exclusion criterion to enable incorporating a broad perspective on acceptance. 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. For the synthesis of the publications, we created a concept matrix (Webster & Watson, 2002).

(b) We assessed the identified determinants with four interviews with practitioners that engage with IPA. We decided on a two-part interview structure. In the first part, 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. Subsequently, we provided the interviewees with the derived potential determinants for adoption. The interviewees were asked to quantify the perceived relevance of the constructs on a 5-point Likert scale of increasing relevance to enhance comparability. In the second part, there was an isolated free discussion of the interviewees' perceived relevance of the identified determinants. The interviews were recorded and transcribed in a denaturalized manner (Azevedo et al., 2017). The total duration of the interviews was 172 min. All dialogues were transcribed to 6,736 words.

(c, d) Subsequently, we related the evaluated determinants formulating hypotheses (see Section Derivation of Determinants and Hypotheses). The hypotheses were formulated analogously to those of UTAUT and relatable models (cf. Appendix 4). Special consideration was given to ensuring that each hypothesis could be evaluated using quantitative measurements established in the literature in the form of questionnaire items.

(e) We evaluated the hypotheses in a preliminary online survey using prolific.com for participant acquisition. Participants were presented with a summary of IPA and the technologies it incorporates, as well as a hypothetical use case. They filled in a structured questionnaire consisting of the measurements relating to the hypotheses. We evaluated the answers using partial least squares structural equation modeling (PLS-SEM). The tests conducted on the measurement model include checking internal consistency, convergent profitability, discriminant validity, and reliability of the indicators (Hair et al., 2011). The preliminary study contained 21 responses.

(f) We created an extended UTAUT model for IPA adoption from the hypotheses validated in the preliminary survey (cf. Venkatesh, 2022). The extended UTAUT model and hypotheses were assessed in the main study (see Model Evaluation and Hypotheses Evaluation). To this end, we recruited native English-speaking employees with daily touch points with processes involving digital technologies from different organizations. 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 intelligent robots. To counteract the problem of careless responses and the associated suboptimal data quality, we used an attention check (Pei et al., 2020). Survey answers were again evaluated with PLS-SEM as it constitutes a solution for small sample sizes and complex models with many constructs and a large number of items (Hair et al., 2019; Willaby et al., 2015). It also causes low bias in reflective measurement models, which approach zero at sample sizes of $n = 100$ and above (Sarstedt et al., 2016). The assessment of the results follows the guidelines by Hair et al. (2014) and Hair et al. (2019). The related calculations were performed via Smart-PLS 3 (Ringle et al., 2015). We used bootstrapping with 500 resamples iterative model optimization (Kock & Hadaya, 2018). For the final derivation of the model parameters, we used bootstrapping with 5000 resamples (Hair et al., 2014).

To further explore the results, we conducted an importance-performance map analysis (Hair et al., 2019). Importance-performance map analysis was developed to prioritize management actions for efficient resource allocation (Martilla & James, 1977). It enables the comparison of the total effects on a defined target construct. Comparison is made in the dimensions of performance and importance in relation to the target construct (Ringle & Sarstedt, 2016).

Table 1 Identified constructs

Construct	Short	Operational Definition
Anxiety	AN	Sum of rational and irrational feelings of fear or anxiety experience when interacting with IPA
Attitude	AT	General affective response to the use of IPA
Effort Expectancy	EE	Degree of perceived ease of use of IPA
Facilitating Conditions	FC	Extent of belief that an organizational and technical infrastructure exists to support the use of IPA
Hedonic Motivation	HM	Joy or pleasure that comes from using IPA
Performance Expectancy	PE	Extent of belief that using IPA will help improve work performance
Perceived Risk	PR	Sum of all perceived risks associated with the use of IPA
Pricing Value	PV	Cognitive trade-off between the perceived benefits and the monetary costs of IPA
Social Influence	SI	Extent of perception that others believe that the individual should use IPA
Trust	TT	The degree of confidence in the specific technology IPA
Transparency	TY	The extent of comprehension and understanding of the internal processes and the output of IPA

Table 2 Characteristics of consulted practitioners

#	Role	Focus	Experience (yrs)
E1	Senior researcher	Hyperautomation, explainable AI	3
E2	Senior researcher	Hyperautomation, explainable AI	4
E3	Partner	Customer relationship management, cloud computing	4
E4	Head of digital process consulting	BPM, RPA, IPA	10

Derivation of determinants and hypotheses

The structured literature review and concept matrix creation resulted in 13 potential determinants for IPA adoption. The concept matrix is shown in Appendix 1. In each contribution, at least one construct of the UTAUT basic model according to Venkatesh et al. (2003) was used, namely, Performance Expectancy ($n=71$), Behavioral Intention ($n=69$), Effort Expectancy ($n=64$), Social Influence ($n=48$), Facilitating Conditions ($n=36$), or Use Behavior ($n=27$). Furthermore, various extensions of the model with the constructs Trust ($n=32$), Attitude Towards Using IPA ($n=25$), Perceived Risk ($n=25$), Pricing Value ($n=13$), Hedonic Motivation ($n=11$), Transparency ($n=8$), and Anxiety ($n=5$) were observed. Table 1 shows the operational definitions of the constructs.

Table 2 shows role, occupational focus, and experience of the practitioners that were consulted for validation of the identified constructs. To this end, the practitioners rated the perceived relevance of each identified determinant on a 5-point Likert scale during the interviews. A rating of 1 indicates low relevance, a rating of 5 indicates high relevance. Table 3 shows their ratings. All median values are above 2.0 (=rather not relevant for adoption). Accordingly, we considered all determinants as potentially relevant for further model development.

The hypotheses were derived analogously to UTAUT and related literature. As consequence of focusing on UTAUT, we included Behavioral Intention and Use Behavior as dependent constructs as they directly relate to technology adoption. Behavioral Intention relates to an employee's subjective willingness to consistently use IPA (Venkatesh et al., 2012). Going beyond the intention, Use Behavior refers to concrete actions to adopt IPA in operational practice (Venkatesh et al., 2012). Appendix 2 shows the relationship between the hypotheses and the literature references.

In addition to the identified determinants, we consider moderators that are diffused in the UTAUT literature, which are age, experience, and gender (Venkatesh et al., 2012). Job level is considered a further moderator, as its relevance is explicitly clarified in the expert interviews. Table 4

Table 3 Ratings of construct relevance by consulted practitioners (1=low relevance, 5=high relevance)

#	AN	AT	EE	FC	HM	PE	PR	PV	SI	TT	TY
E1	5	3	2	4	1	5	4	4	3	4	4
E2	5	4	2	4	3	5	4	4	2	5	2
E3	5	5	3	2	4	5	3	5	5	4	1
E4	4	4	5	4	3	5	3	5	5	5	3
Median	5	4	2.5	4	3	5	3.5	4.5	4	4.5	2.5

Table 4 Identified hypotheses

#	Hypotheses	#	Hypotheses	#	Hypotheses
1a	PE $\overset{+}{\rightarrow}$ BI	**4f**	FC * AGE, EXP, GDR → BI	**7 h**	TT * AGE, EXP, GDR → EE
1b	PE $\overset{+}{\rightarrow}$ AT	**4 g**	FC * AGE, EXP, GDR → EE	**7i**	TT * AGE, EXP, GDR → PE
1c	PE * AGE, GDR, JOL → BI	**4 h**	FC * AGE, EXP, GDR → PE	**7j**	TT * AGE, EXP, GDR → PR
1d	PE * AGE, GDR, JOL → AT	**5a**	AT $\overset{+}{\rightarrow}$ BI	**8**	TY $\overset{+}{\rightarrow}$ TT
2a	EE $\overset{+}{\rightarrow}$ BI	**5b**	AT $\overset{+}{\rightarrow}$ UB	**9a**	AN $\overset{-}{\rightarrow}$ BI
2b	EE $\overset{+}{\rightarrow}$ PE	**6a**	PR $\overset{-}{\rightarrow}$ BI	**9b**	AN $\overset{+}{\rightarrow}$ PE
2c	EE $\overset{+}{\rightarrow}$ AT	**6b**	PR $\overset{-}{\rightarrow}$ PE	**9c**	AN $\overset{-}{\rightarrow}$ EE
2d	EE * AGE, GDR, EXP → BI	**6c**	PR $\overset{-}{\rightarrow}$ AT	**9d**	AN * AGE, EXP, GDR, JOL → BI
2e	EE * EXP → AT	**6d**	PR * AGE, GDR → BI	**9e**	AN * AGE, EXP, GDR, JOL → PE
3a	SI $\overset{+}{\rightarrow}$ BI	**6e**	PR * AGE, GDR → PE	**9f**	AN * AGE, EXP, GDR, JOL → EE
3b	SI $\overset{+}{\rightarrow}$ AT	**6f**	PR * AGE, GDR → AT	**10a**	HM $\overset{+}{\rightarrow}$ BI
3c	SI * AGE, EXP, GDR, JOL → BI	**7a**	TT $\overset{+}{\rightarrow}$ BI	**10b**	HM * AGE, EXP, GDR, JOL → BI
3d	SI * AGE, EXP, GDR, JOL → AT	**7b**	TT $\overset{+}{\rightarrow}$ AT	**11a**	PV $\overset{+}{\rightarrow}$ BI
4a	FC $\overset{+}{\rightarrow}$ UB	**7c**	TT $\overset{+}{\rightarrow}$ EE	**11b**	PV * AGE, EXP, GDR, JOL → BI
4b	FC $\overset{+}{\rightarrow}$ BI	**7d**	TT $\overset{+}{\rightarrow}$ PE	**12a**	BI $\overset{+}{\rightarrow}$ UB
4c	FC $\overset{+}{\rightarrow}$ EE	**7e**	TT $\overset{-}{\rightarrow}$ PR	**12b**	BI * EXP → UB
4d	FC $\overset{+}{\rightarrow}$ PE	**7f**	TT * AGE, EXP, GDR → BI		
4e	FC * AGE, EXP → UB	**7 g**	TT * AGE, EXP, GDR → AT		

$\overset{-}{\rightarrow}$ significant negative influence, $\overset{+}{\rightarrow}$ significant positive influence, * moderating influence

Age (AGE), Anxiety (AN), Attitude (AT), Behavioral Intention (BI), Effort Expectancy (EE), Experience (EXP), Facilitating Conditions (FC), Gender (GDR), Hedonic Motivation (HM), Job Level (JOL), Performance Expectancy (PE), Perceived Risk (PR), Price Value (PV), Social Influence (SI), Trust (TT), Transparency (TY), Use Behavior (UB)

summarizes the formulated hypotheses, which are outlined in the following.

We assume a positive influence of Performance Expectancy on Behavioral Intention for two reasons (**H1a**). First, this influence exists in the UTAUT reference model and in IPA-related work, such as on RPA (Wewerka et al., 2020) and chatbots (Danckwerts et al., 2020; Eißer et al., 2020; Laumer et al., 2019; Meyer-Waarden et al., 2020). Second, the practical application of IPA demonstrates significant advantages in terms of efficiency and cost savings. Due to the ability to cost-effectively automate repetitive tasks, a connection to the intention of using IPA is assumed. The degree to which IPA is expected to be useful or powerful to leverage performance may positively relate to the Attitude towards using IPA (Dwivedi et al., 2019) (**H1b**). This applies in particular to the acceptance of software solutions by employees (Amin et al., 2016). Several identified contributions show the influence of Performance Expectancy on Attitude of technology in general as well as for AI-based tools (Liu et al., 2019; e.g., Pan et al., 2019). We adopt the assumption of moderating effects of Age and Gender on Performance Expectancy and Attitude in UTAUT (Venkatesh et al., 2003).

Further, we consider Job Level as a moderator for the effects of Performance Expectancy (**H1c, H1d**). The interviewees explained that a critical point would exist where Performance Expectancy is so high that the respective technology would be perceived as a threat to employment, hindering the adoption.

Analogous to Performance Expectancy, we assume a positive influence of Effort Expectancy on Behavioral Intention for two reasons (**H2a**). First, we orient towards the UTAUT reference model. Further, we identified contributions finding this influence specifically for IPA (Eißer et al., 2020; e.g., Wewerka et al., 2020). Second, since IPA often operates at the user level of software via robots, there is no need for costly and extensive modifications related to the software associated with the process to be automated (Syed et al., 2020). In line with the idea of automation and more efficient resource utilization, we also assume a positive influence of Effort Expectancy on Performance Expectancy in the context of IPA (**H2b**). The influence of Effort Expectancy on Performance Expectancy was observed in the identified contributions investigating IPA (Eißer et al., 2020; e.g., Wewerka et al., 2020). The degree to which IPA use is perceived as complex compared to other technologies could

also positively influence the Attitude towards the technology (Dwivedi et al., 2019) (**H2c**). The influence between Effort Expectancy and Attitude has been observed in adoption-related literature concerning AI-based tools (Cao et al., 2021; e.g., Pan et al., 2019). We incorporate the assumption that Age, Gender, and Experience moderate the effect from Effort Expectancy on Behavioral Intention from the UTAUT reference model (Venkatesh et al., 2003) (**H2d**). Further, the interviewees mentioned that Effort Expectancy and its effects strongly depend on users' experience influencing their Attitude (**H2e**). For instance, Effort Expectancy in the use of IPA tools, tends to be lower if the user has experience with comparable technologies.

We posit a positive influence of Social Influence on Behavioral Intention (**H3a**). Consistent with the UTAUT reference model, identified contributions indicate this influence regarding AI-based tools (Aboelmaged, 2010; Cox, 2012; Gao et al., 2015; Handoko et al., 2018; Hsu et al., 2014; Lee & Song, 2013; Lee, 2009; Li et al., 2020; Slade et al., 2015; Wang et al., 2015). UTAUT meta-studies corroborate this impact (Dwivedi et al., 2019; e.g., Williams et al., 2015). Analogously, we assume an influence of Social Influence on Attitude (**H3b**). We justify the assumption by the potential influence of third parties who have adopted or rejected the respective technology on the attitudes of potential users (Dwivedi et al., 2019). The influence of Social Influence on Attitude has been observed in literature on RPA (e.g., Wewerka et al., 2020) and AI (e.g., Peters et al., 2020). We adopt Age, Gender, and Experience as moderators on the relations of Social Influence on Behavioral Intention and Attitude from the UTAUT reference model (Venkatesh et al., 2003). Additionally, the interviewees emphasized that Social Influence towards IPA adoption is exerted less frequently at the same hierarchical level but primarily between Job Levels (**H3c**, **H3d**). It can be inferred that the influence of Social Influence increases with the number of hierarchical levels above.

Regarding Facilitating Conditions, we assume a positive influence on Use Behavior (**H4a**). Facilitating Conditions such as the management of high data volume and consistent data quality comprise major challenges in the implementation of AI-based automation (Jyoti & Szurley, 2021). Also, Facilitating Condition influences Use Behavior in the UTAUT reference model (Venkatesh et al., 2003). The influence has additionally been proven in a meta-analysis (Williams et al., 2015). In the UTAUT reference model, Facilitating Conditions do not directly influence Behavioral Intention. Venkatesh et al. (2003) argued that the explanatory power of Facilitating Conditions on Behavioral Intention could only be demonstrated if Performance Expectancy and Effort Expectancy are not included in the model. Dwivedi et al. (2019) point out that this limitation does not hold true in every configuration, which is supported by the results of our structured literature review. In the context of UTAUT2, Venkatesh et al. (2012) argued that individuals with access to an advantageous set of Facilitating Conditions exhibit a higher willingness to adopt a technology. Therefore, the positive influence of Facilitating Conditions on Behavioral Intention cannot be excluded in the context of IPA (**H4b**). Furthermore, we assume a positive influence of Facilitating Conditions on Effort Expectancy (**H4c**). This is justified by Facilitating Conditions being a direct determinant of Effort Expectancy in the acceptance of new software solutions by employees (Amin et al., 2016) and technology acceptance in general (Venkatesh & Bala, 2008). Moreover, Facilitating Conditions could exert a positive influence on Performance Expectancy (**H4d**). This is justified by the provision of appropriate training and a sufficiently high-quality technical and organizational infrastructure, which assist potential users in gaining clarity about the actual system performance (Chatterjee & Bhattacharjee, 2020). The implied effect between Facilitating Conditions and Performance Expectancy has been observed in AI-based tools (e.g., van Hung et al., 2021), especially in the business context (e.g., Cao et al., 2021). We adopt the moderating effects regarding Facilitating Conditions according to the UTAUT reference model (**H4e-h**).

In the UTAUT reference model, there is no significant effect on Behavioral Intention or Use Behavior due to potential overlaps with Performance Expectancy and Effort Expectancy (Venkatesh et al., 2003). We do include positive influences as more recent research indicates that Attitude can be a relevant determinant in the adoption and usage of innovative technologies (Dwivedi et al., 2017) (**H5a**). Furthermore, it has been demonstrated that Attitude can be a direct determinant of Behavioral Intention in the acceptance of software by employees (Amin et al., 2016; Morris et al., 2005; Pan et al., 2019). The positive influence of Attitude on Use Behavior is examined separately **(H5b)**. A general aversion towards algorithms inherent to AI-based tools may have a significant impact on IPA adoption (Berger et al., 2021). Usage behavior is thus influenced by Attitude (Venkatesh, 2022).

We assume a negative influence of Perceived Risk on Behavioral Intention, Performance Expectancy, and Attitude in the context of IPA adoption. Potentially Perceived Risks are manifold, such as financial risks or Performance Risks in case IPA works less efficiently than assumed. The negative influence of Perceived Risk on Behavioral Intention has been observed in a large number of identified contributions on IPA (e.g., Huang & Wang, 2009; Laumer et al., 2019) and generally in AI-based tools (**H6a**) (Gao et al., 2015; Jianbin & Jiaojiao, 2013; M.-C. Lee, 2009; J. Li et al., 2019; Slade et al., 2015). In addition to the absolute benefit (Davis, 1989), Performance Expectancy also includes the relative advantage (Moore & Benbasat, 1991)

of technologies in the form of economic profitability, social prestige or other benefits (Rogers, 2010) compared to previous technologies (Oechslein et al., 2014). It is therefore intuitive that the corresponding, opposite Perceived Risk can have a negative impact on Performance Expectancy (**H6b**) (Hein et al., 2018; e.g., Laumer et al., 2019). The assumption of a negative influence of Perceived Risk on Attitude is due to a generic tendency towards risk aversion of AI-users in business (Pal et al., 2018; e.g., Pan et al., 2019) (**H6c**). In terms of moderators, we adopt the consideration of Age and Gender from UTAUT (**H6d-f**) (Venkatesh et al., 2003).

We assume a positive influence of Trust on Behavioral Intention. This is due to the overall important role of Trust in the intention to use AI (**H7a**) (e.g., Jyoti & Szurley, 2021). The identified contributions show a positive influence of Trust on Behavioral Intention in AI adoption in general and specifically for IPA (Danckwerts et al., 2020; Liu et al., 2019; Noonpakdee, 2020; Peters et al., 2020; Vimalkumar et al., 2021; Wanner et al., 2021). Analogously, we assume a positive influence on Attitude (**H7b**) (Liu et al., 2019; Pitardi & Marriott, 2021; Wanner et al., 2021; Zhang et al., 2019), Effort Expectancy (**H7c**) (Wewerka et al., 2020), and Performance Expectancy (**H7d**) (Laumer et al., 2019; Shin, 2021; Vimalkumar et al., 2021). Perceived Risk is defined as a component of trust models (Choi & Ji, 2015). Interviewees stated that the establishment of Trust may decrease Risk Perception. Identified contributions also indicate a negative relationship of Trust on Perceived Risk (**H7e**) (Das & Teng, 2004; Kaplan et al., 1974). Aligning with related literature, we assume an influence of Age (Herrando et al., 2019; Liébana-Cabanillas et al., 2014) and Gender (Buchan et al., 2008) on the influence of Trust. Additionally, the interviewees indicated moderating effects of Experience (**H7f-j**).

The creation of Transparency influences adopting AI-related technology (Bauer et al., 2023; Herm et al., 2022). Several contributions show that creating Transparency of intelligent systems can significantly increase Trust with positive effects on adoption (**H8**) (Chakraborti et al., 2020; Peters et al., 2020; Shin, 2021).

Several contributions show a negative influence of Anxiety for the adoption of RPA (Syed et al., 2020). Anxiety can be multi-faceted and, for example, be directed to working with robots (Venkatesh et al., 2003), or job loss (Liang & Lee, 2017; Parkes, 2002). We find evidence supporting a negative influence of Anxiety on Behavioral Intention (**H9a**) (Kim et al., 2017). On this basis, we also assume a positive influence of Anxiety on Performance Expectancy as employees fear replacement by AI that can perform human tasks. That is, employees expect human-like performance of AI-related technology indicating a positive relation with Anxiety (**H9b**). Further, we align with established findings assuming a negative influence of Anxiety on Effort Expectancy (**H9c**) (Venkatesh, 2000; Venkatesh & Bala, 2008). Based on the interviews, we assume moderating effects of Age, Experience, Gender, and Job Level on the relationships of Anxiety (**H9d-f**). For example, employees with higher Job Level may have lower Anxiety over losing their jobs to AI-related technology as they have a lower proportion of repetitive, automatable tasks.

Opposed to considerations on Anxiety, investigating the construct of Hedonic Motivation shifts the perspective to positive consequences of job automation. For example, delegating tedious, repetitive tasks to AI-based technology may be considered a relief for employees with effects on their adoption propensity and Behavioral Intention (**H10a**). Automation of those tasks leads to more resources for more complex tasks (Wewerka et al., 2020). Following Venkatesh et al. (2012), we assume a moderating effect of Age, Experience, and Gender in this regard. Additionally, an interviewee mentioned that the appreciation of automating repetitive tasks to leave resources for complex tasks increases with Job Level. Thus, we also incorporate Job Level as moderator (**H10b**).

As IPA promises high cost-saving potential due to automation, we assume a positive influence of Price Value on adoption on the Behavioral Intention. Even if employees, do not directly have to bear the costs of IPA (Venkatesh et al., 2012), Price Value influences their decision to adopt the technology, for example, if employees are remunerated on the basis of adherence to specific budgets or other traditional financial metrics (**H11a**) (DeFeo et al., 2010). We adopt the assumption that Age and Gender moderate this relation from Venkatesh et al. (2012). Additionally, we assume a moderating effect of Experience and Job Level based on the interviews (**H11b**).

Referring to the UTAUT reference model, we assume a positive influence of Behavioral Intention on Use Behavior (**H12a**) (Venkatesh et al., 2003). The influence is confirmed in several identified contributions on the IPA-related technologies, such as RPA (Wewerka et al., 2020) and chatbots (Eißer et al., 2020; Laumer et al., 2019) as well as in more generic work on the adoption of AI-based tools (Chatterjee & Bhattacharjee, 2020; Jianbin & Jiaojiao, 2013; Sohn & Kwon, 2020; Vimalkumar et al., 2021). Following Venkatesh et al. (2012), we also assume moderating effects of Experience on this relationship (**H12b**).

Model evaluation

The measurement model for the hypotheses was created in analogy to UTAUT and related models. It initially consisted of 56 items and serves the purpose of quantifiability. Appendix 3 shows all items and the literature references from which they originate. The preliminary online study was used for initial hypotheses validation. We checked for

internal consistency using Cronbach's Alpha (Cα) and Composite Reliability (CR) (Bacon et al., 1995; Cronbach, 1951). We used the Average Variance Extracted (AVE) to assess the convergent validity. The reliability of the indicators was checked using the item loadings. Since preliminary studies can be regarded as exploratory studies (Wanner et al., 2021) and a relatively small sample size was available, the accepted rounded threshold value of the indicator loadings was reduced from the generally proposed threshold value of 0.7 (Hair et al., 2011) to 0.5 (e.g., Urbach & Ahlemann, 2010). In addition, discriminant validity was tested using the Fornell-Larcker (FL) criterion of (Fornell & Larcker, 1981). We iteratively removed items with loadings below 0.5. Overall, three items were removed, which are marked in Appendix 3. A strict positive change in the remaining defined performance metrics was observed. The resulting evaluation of the measurement model can be found in Table 5.

All determinants fulfilled the evaluation criteria, except Facilitating Conditions, for which the FL criterion could not be met. However, we decided to keep Facilitating Conditions for evaluation in the main study for two reasons. First, Facilitating Conditions are of specific practical relevance. Three interviewees stressed their role entailing practical implications for the lasting adoption and operational integration of IPA. Second, for consistency with previous research on the adoption of IPA, BPM and RPA, and AI, we would like to further explore Facilitating Conditions to leverage potential for theoretical implications in line with related research (Ajzen, 1991; Moore & Benbasat, 1991; Thompson et al., 1991; Venkatesh et al., 2003).

The sample of the main study is composed of subjects who use different technologies for their jobs daily. Prestudy 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. Table 6 shows the distribution of the participants' characteristics. Among other characteristics, we asked participants to indicate their experience with process automation and robotic process automation, which serve as proxies for lightweight and heavyweight automation (Engel et al., 2022).

The evaluation of the measurement model is carried out analogously to the preliminary study via the path coefficients Cα, CR, and AVE and the FL criterion. Additionally, we calculated determination coefficients (R^2) and cross-validation (Q^2). The metrics are shown in Table 7. The R^2 of Attitude (0.75) can be estimated as substantial, the R^2 of Behavioral Intention (0.72) as moderate and the $R^2$of Effort Expectancy (0.48), Use Behavior (0.44), Performance Expectancy (0.42), Perceived Risk (0.34), and Trust (0.26) as weak (Hair et al., 2011). The relevance of Attitude (0.51) and Behavioral Intention (0.57) attributed to Q^2 can be classified as high, of Effort Expectancy (0.33), Perceived Effort (0.32) and Use Behavior (0.38) as moderate and of Perceived Risk (0.16) and Trust (0.15) as low (Hair et al., 2019).

Hypothesis evaluation

Figure 2 visualizes the structural model including the path coefficients of each hypothesis. The structural model was optimized iteratively to match the defined performance metrics. We find significant positive effects of Performance

Table 5 Evaluation metrics of the preliminary study

	AN	AT	BI	EE	FC	HM	PE	PR	PV	SI	TT	TY
Cα	0.90	0.96	0.96	0.90	0.76	0.90	0.96	0.80	0.87	0.91	0.93	0.81
CR	0.90	0.97	0.98	0.94	0.83	0.93	0.97	0.83	0.92	0.94	0.94	0.88
AVE	0.61	0.86	0.93	0.83	0.51	0.83	0.86	0.51	0.79	0.79	0.74	0.64
AN	**0.78**	−0.42	−0.22	−0.26	−0.21	−0.41	−0.17	0.74	−0.10	−0.03	−0.28	−0.17
AT		**0.93**	0.84	0.70	0.69	0.64	0.85	−0.64	0.66	0.52	0.84	0.85
BI			**0.96**	0.73	0.66	0.57	0.70	−0.48	0.59	0.65	0.75	0.79
EE				**0.91**	0.79	0.57	0.77	−0.42	0.63	0.72	0.64	0.69
FC					**0.71**	0.60	0.80	−0.32	0.75	0.85	0.58	0.68
HM						**0.91**	0.52	−0.59	0.33	0.56	0.59	0.59
PE							**0.93**	−0.32	0.74	0.65	0.78	0.82
PR								**0.71**	−0.26	−0.04	−0.50	−0.48
PV									**0.89**	0.56	0.56	0.78
SI										**0.89**	0.49	0.55
TT											**0.86**	0.81
TY												**0.80**

Table 6 Characteristics of participants

Category	*n*	%
Age (years)		
< 20	3	1.8
20–24	45	26.8
25–29	58	34.5
30–34	26	15.5
35–39	13	7.7
40–44	9	5.4
45–49	3	1.8
50–54	5	3.0
55–59	4	2.4
≥ 60	2	1.2
Sum	168	100
Gender		
Male	94	56.0
Female	72	42.9
Diverse	2	1.2
Sum	168	100
Experience PA (years)		
None	98	58.3
1–3	53	31.5
4–6	11	6.5
7–9	2	1.2
≥ 10	4	2.4
Sum	168	100
Experience RPA (years)		
None	102	60.7
1–3	53	31.5
4–6	9	5.4
7–9	1	0.6
≥ 10	3	1.8
Sum	168	100
Occupation		
Blue-collar	36	21.4
White-collar	94	56.0
Management	36	21.4
Top management	2	1.2
Sum	168	100

Expectancy and Effort Expectancy on Attitude (**H1b** and **H2c**). Also, results show a significant influence of Trust on Attitude (**H7g**). For the constructs Effort Expectancy, Facilitating Conditions, and Trust, significant positive effects on Performance Expectancy can be demonstrated (**H2b**, **H4d**, and **H7d**). In addition, a significant positive relationship between Facilitating Condition and Effort Expectancy can be identified (**H4c**). There are significant negative effects of Perceived Risk on Attitude (**H6c**), of Trust on Perceived Risk (**H7e**), and of Anxiety on Effort Expectancy (**H9c**). Behavioral Intention is positively influenced by Attitude (**H5a**) as well as Hedonic Motivation (**H10a**) with statistical significance. Transparency has a direct significant effect on Trust (**H8**). The assumed influence from Behavioral Intention on Use Behavior (**H12a**) can also be confirmed with significance.

The moderating effects are not visualized to provide more clarity to the figure. None of the hypotheses related to the moderating properties of Age, Gender, Experience, and Job Level can be fully confirmed. Of the effects of Age, Gender, and Experience on Trust (**H7j**), only the latter can be confirmed. Of the effects of all defined moderators between Price Value and Behavioral Intention (**H11b**), a significant positive effect of Job Level and a significant negative effect of Experience can be demonstrated. Furthermore, statistically significant positive effects of Experience on Effort Expectancy and Use Behavior can be identified. All other hypotheses are rejected. The indirect and total effects are presented in Appendix 4 (cf. Hair et al., 2019). We use the total effects as basis for the importance-performance map analysis to relate the determinants in terms of performance and importance (Hair et al., 2019).

Figure 3 shows the unstandardized importance and performance for the four constructs that are most affected by other constructs, that is Behavioral Intention, Attitude, and Effort Expectancy. It includes all constructs with significant total effects on these four constructs. Dashed lines represent average importance and performance delineating quadrants, which indicate priority areas (Martilla & James, 1977). In the first quadrant titled "*Possible overkill*" comparably less important determinants receive high performance attention. The focus should be reduced to leverage capacities to foster more important determinants. The second quadrant titled "*Keep up the good work*" covers important determinants that are already highly prioritized in terms of performance. Opposed to that, quadrant three includes determinants of low importance and low performance-related attention, the quadrant is thus titled "*Low priority*." Quadrant four, titled "*Concentrate here*," reveals which determinants are supposed to receive most management attention to leverage performance as covered determinants are of high importance.

Our results show an overarching role of Trust as performance and importance are high for effects on Behavioral Intention, Attitude and Effort Expectancy. To foster IPA adoption, management should keep a focus on trust. Interestingly, Trust falls below average importance in terms of effects on Use Behavior as Attitude and Behavioral Intention are rated more important influential factors. Moreover, Transparency tightly connects to Trust, but is considered an overall less important influential factor for all four constructs. One reason for this may be that transparency alone is considered rather less important for IPA adoption. Also, in practice, Trust depends on various determinants additional to transparency (X. Li et al., 2008). Opposed to the

Table 7 Evaluation metrics of the main study

	AN	AT	BI	EE	FC	HM	PE	PR	PV	SI	TT	TY
R^2		0.75	0.72	0.48			0.42	0.34			0.26	
Q^2		0.51	0.57	0.33			0.32	0.16			0.15	
Cα	0.836	0.895	0.915	0.862	0.805	0.927	0.938	0.714	0.904	0.855	0.869	0.709
CR	0.881	0.923	0.946	0.915	0.861	0.954	0.953	0.821	0.940	0.903	0.902	0.837
AVE	0.554	0.706	0.854	0.783	0.555	0.873	0.802	0.533	0.839	0.702	0.606	0.632
AN	**0.744**	−0.522	−0.381	−0.541	−0.399	−0.419	−0.349	0.477	−0.233	−0.219	−0.420	−0.388
AT		**0.840**	0.759	0.564	0.543	0.656	0.708	−0.506	0.506	0.483	0.736	0.531
BI			**0.924**	0.517	0.559	0.585	0.667	−0.284	0.356	0.529	0.547	0.502
EE				**0.885**	0.503	0.558	0.499	−0.175	0.218	0.402	0.392	0.586
FC					**0.745**	0.387	0.493	−0.225	0.236	0.522	0.463	0.491
HM						**0.934**	0.473	−0.288	0.203	0.340	0.501	0.476
PE							**0.896**	−0.275	0.361	0.499	0.515	0.458
PR								**0.730**	−0.372	−0.130	−0.556	−0.260
PV									**0.916**	0.275	0.395	0.227
SI										**0.838**	0.385	0.290
TT											**0.778**	0.507
TY												**0.795**

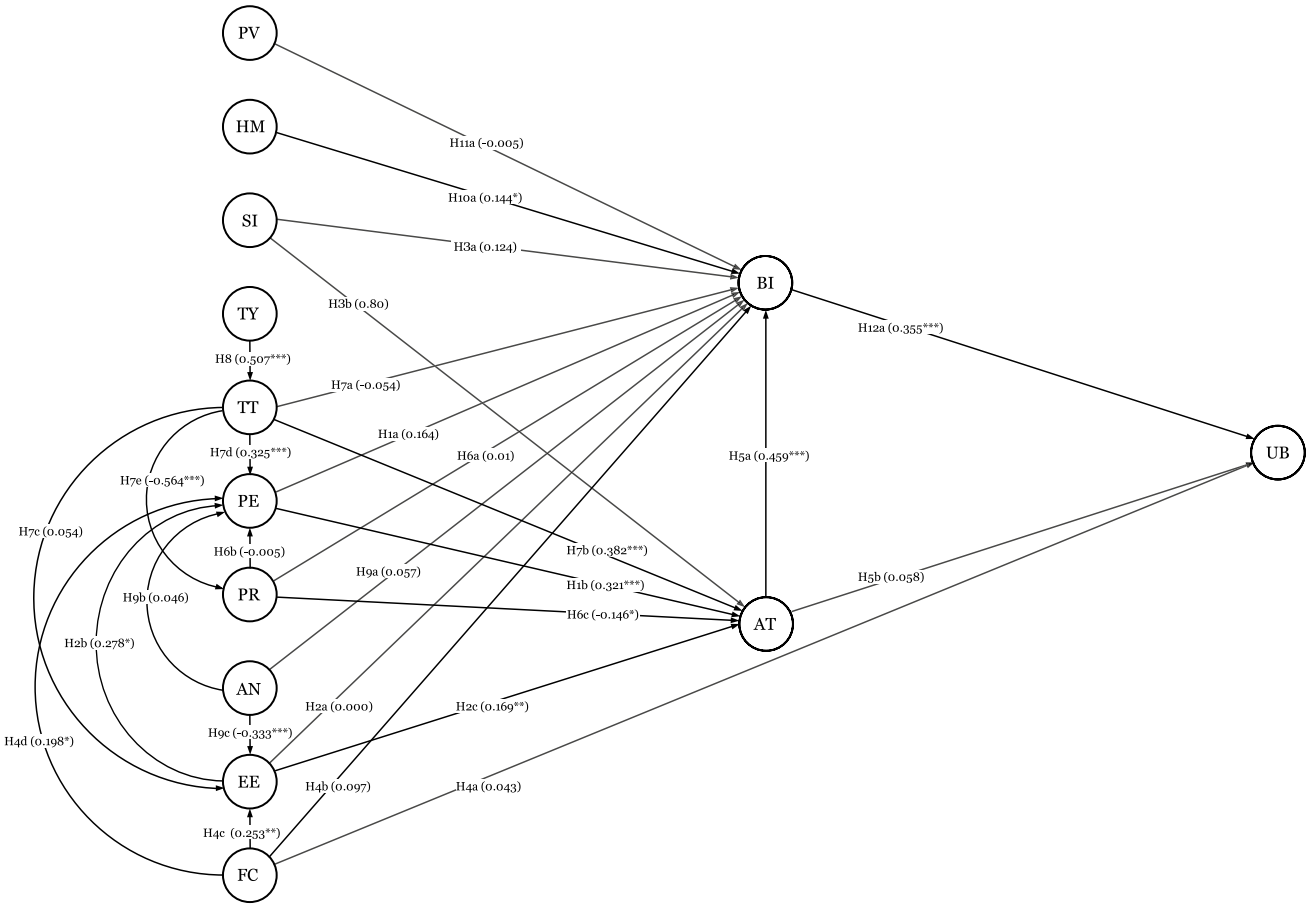
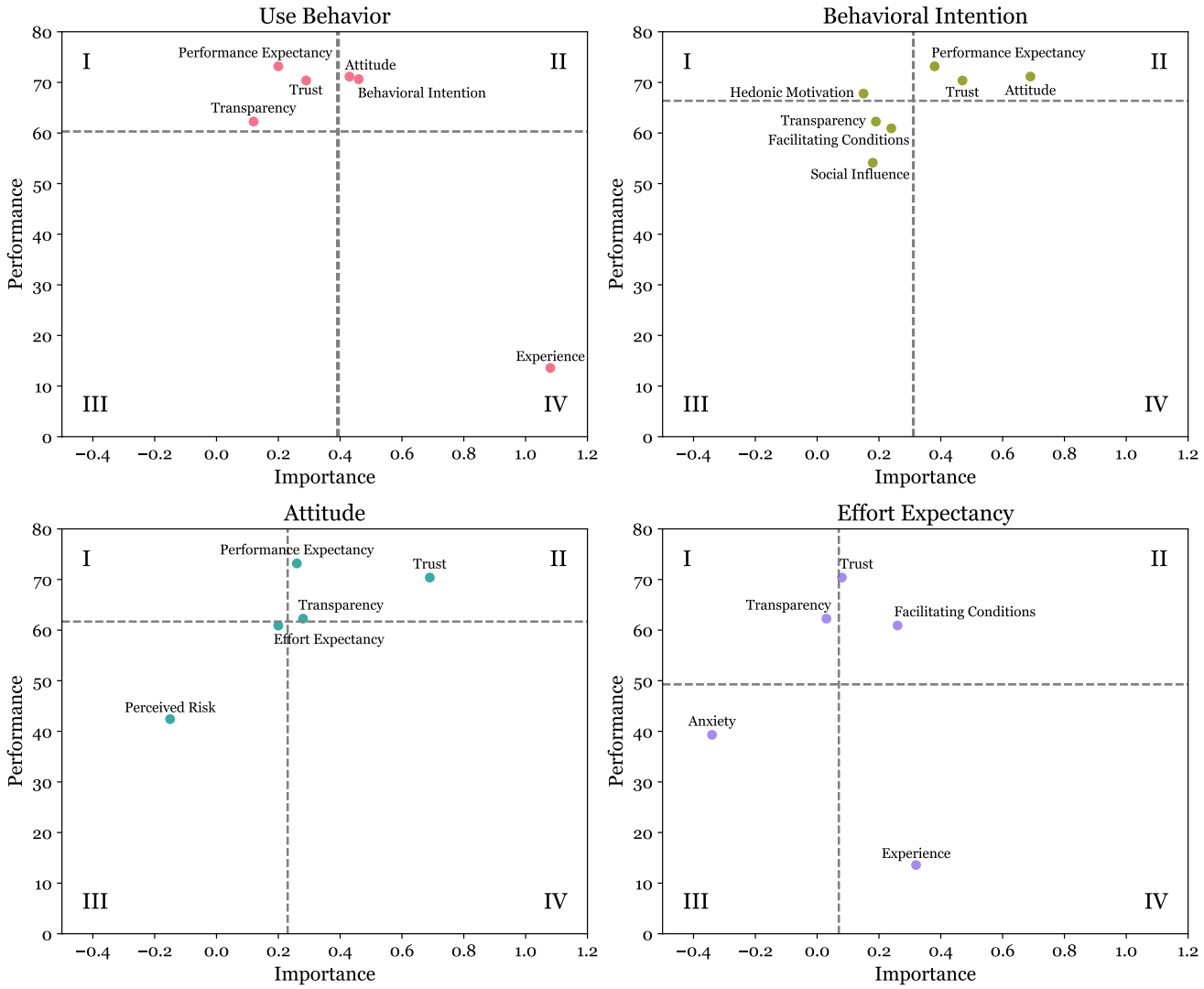


Fig. 2 Structural model



I: "Possible overkill", II: "Keep up the good work", III: "Low priority", IV: "Concentrate here" (Martilla & James, 1977)

Fig. 3 Importance-performance map analysis plots for total effects

high importance and performance Trust, Perceived Risk and Anxiety fall into the third quadrant ("Low priority") for Attitude and Effort Expectancy, respectively. Perceived Risk and Anxiety are each considered less important and lower in performance than Transparency. Management should thus rather prioritize the creation of transparency to enhance IPA adoption through trust. In accordance, Performance Expectancy is considered relevant and high in performance as an influential factor for Attitude and Behavioral Intention, so that it belongs to the second quadrant, respectively.

Furthermore, we find that organizations should prioritize experience in terms of performance to influence Use Behavior and Effort Expectancy towards IPA adoption. Management attention should be focused on potential adopters' experience to leverage individual needs for IPA adoption.

Facilitating conditions play a special role for Effort Expectancy, as they are rated highly in terms of both performance and importance. A key benefit of IPA is the reduction of individual effort, so organizations should focus on setting up Facilitating Conditions to reduce the effort associated with IPA implementation. In terms of its influence on use behavior, Facilitating Conditions are considered less important than Trust, Attitude, and Behavioral Intentions.

Discussion

Implications for theory and practice

With our research, we respond to the call for work system-oriented research by Engel et al. (2022) We focus on how to embed IPA in organizations from a socio-technical perspective particularly addressing IPA adoption. Based on an extended UTAUT model, we identify factors that facilitate the embedding of IPA, which we discuss in the following with regards to implications for theory and practice.

We identified a direct positive effect of Behavioral Intention on Use Behavior. This implies that the direct positive effect of Behavioral Intention on actual Use Behavior defined in UTAUT by Venkatesh et al. (2003) might be also valid in the IPA context. The comparatively strong and direct effect of Attitude on Behavioral Intention also suggests that the Behavioral Intention might be dependent on Attitude. In addition, the indirect effect of Attitude on Use Behavior suggests that actual usage behavior may be dependent on attitudes towards IPA in addition to Behavioral Intention. Dwivedi et al. (2019) were able to make comparable inferences from direct effects of Attitude on Behavioral Intention in their UTAUT meta-study. The positive effect of Experience on Use Behavior implies that potential adopters who have Experience are more likely to use IPA than workers without prior Experience. The positive direct effect of Experience on Effort Expectancy also implies that potential adopters who have Experience 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 Anxiety on Effort Expectancy implies that fear of IPA or its associated technologies may have a negative impact on Effort Expectancy. This suggests that potential users initially perceive the complexity of use to be comparatively high due to a perception bias caused by Anxiety, and that this effect decreases with increasing experience with the technology.

The direct influence of Effort Expectancy on Performance Expectancy implies that it could be relevant in the context of IPA how high the perceived effort of IPA is to actually be able to exploit the potential for improvement and performance. Performance Expectancy increases with ease of use. Analogous correlations have been confirmed in various contexts since the definition of TAM (Davis, 1985; Pan et al., 2019).

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 Gender 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, should be conducted.

Consequently, our study presents a sizeable contribution in the form of an enhanced UTAUT model for IPA. Our model builds upon existing UTAUT frameworks, inheriting core elements while introducing new dimensions that broaden its applicability. By integrating these advancements, our model establishes a robust platform for the development of future UTAUT-based models on IPA. This makes it an important tool for researchers aiming to explore and expand the theoretical and practical applications of technology acceptance models for IPA. Despite the theoretical lens of our research, we further infer several actionable implications for both theory and practice as outlined in the following. Table 8 provides a summary of these inferred implications and relates these to the model hypotheses that were confirmed with statistical significance.

Cultivate a positive attitude towards IPA

Overall, we find Attitude to be a potent determinant of IPA adoption due to its direct effects on both Behavioral Intention and Use Behavior. We were able to confirm the high relevance of Attitude in technology adoption as emphasized by Dwivedi et al. (2019). Accordingly, we support the proposal to implement Attitude as an integral part of the UTAUT model for future acceptance research (Dwivedi et al., 2019). There are direct negative effect of Anxiety on Effort Expectancy. This implies that fear of IPA or its associated technologies may have a negative impact on Effort Expectancy. This suggests that potential users initially perceive the complexity of use to be comparatively high due to a perception bias caused by Anxiety, and that this effect decreases with increasing experience with the technology.

To cultivate a positive Attitude towards IPA and reduce Anxiety in practice, Performance Expectancy could be improved by communicating the capabilities of IPA through documentation about the technology (Koh et al., 2010), previous achievements, use cases of automation (J.-H. Lee & 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 to showcase entailed benefits. It was shown that software robots are mainly adopted and widely developed in organizations where top management integrates the solution into the corporate culture with effects on overall attitude

Table 8 Summary of results and implications

Implications	#	Hypotheses
Cultivate a positive attitude towards IPA	**1b**	PE $\overset{+}{\rightarrow}$ AT
	2c	EE $\overset{+}{\rightarrow}$ AT
	5a	AT $\overset{+}{\rightarrow}$ BI
	6c	PR $\overset{-}{\rightarrow}$ AT
	7 g	TT * AGE, EXP, GDR → AT
	12a	BI $\overset{+}{\rightarrow}$ UB
Establish facilitating conditions	**4c**	FC $\overset{+}{\rightarrow}$ EE
	4d	FC $\overset{+}{\rightarrow}$ PE
	2b	EE $\overset{+}{\rightarrow}$ PE
Mind experience of users	**11b**	PV * AGE, EXP, GDR, JOL → BI
	7j	TT * AGE, EXP, GDR → PR
	9c	AN $\overset{-}{\rightarrow}$ EE
	10a	HM $\overset{+}{\rightarrow}$ BI
Transparency is no end in itself	**8**	TY $\overset{+}{\rightarrow}$ TT
	7d	TT $\overset{+}{\rightarrow}$ PE
	7e	TT $\overset{-}{\rightarrow}$ PR

$\overset{-}{\rightarrow}$ significant negative influence, $\overset{+}{\rightarrow}$ significant positive influence, * moderating influence

Age (AGE), Anxiety (AN), Attitude (AT), Behavioral Intention (BI), Effort Expectancy (EE), Experience (EXP), Facilitating Conditions (FC), Gender (GDR), Hedonic Motivation (HM), Job-Level (JOL), Performance Expectancy (PE), Perceived Risk (PR), Price Value (PV), Social Influence (SI), Trust (TT), Transparency (TY), Use Behavior (UB)

(Willcocks et al., 2015). Furthermore, a positive Attitude can be cultivated by stressing the importance of and counteracting prevalent Perceived Risk and Anxiety. Perceived Risk'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 negative influence of Anxiety should be remediated through continuous sensitization. In particular, Anxiety about losing one's job due to automation should be addressed to foster IPA adoption.

Establish facilitating conditions

We find that organizations can influence IPA adoption establishing Facilitating Conditions. Specifically, our results show direct effects of Facilitating Conditions on Effort Expectancy and Performance Expectancy and indirect effects on Attitude. These effects suggest that organizations should provide appropriate tools and support employees in the use of IPA. The establishment of hands-on training to demonstrate IPA use and entailed advantages of automation constitutes an exemplary Facilitating Condition (Alshare & Lane, 2011; Sabherwal et al., 2006). Helpdesks can be established to ensure continuous support for both initial or ongoing IPA use (Coeurderoy et al., 2014). To influence Performance Expectancy, Effort Expectancy, and Attitude positively, infrastructures should facilitate IPA integration into daily operational practice. Additionally, designing user-friendly interfaces of IPA tools supports its adoption (Zuiderwijk et al., 2015).

Mind experience of users

Our results show that IPA adoption depends on user characteristics, in particular Experience. The positive effect of Experience on Use Behavior implies that potential adopters who have Experience are more likely to use IPA than workers without prior Experience. The positive direct effect of Experience on Effort Expectancy also implies that potential adopters who have Experience perceive the use of the technology to be easier than workers without related prior knowledge. Furthermore, the moderating effect of Experience between Price Value and Behavioral Intention suggests that Price Value is increasingly negatively perceived by individuals with Experience. Additionally, the observable positive moderating effects of Job Level between Pricing Value and Behavioral Intention and Pricing Value and Use Behavior imply that as Job Level increases, the Pricing

Value of the technology is increasingly perceived positively or weighted more highly.

This entails that providing job-level adequate training on the capabilities of IPA and intelligent systems or machine learning in general could improve the overall adoption of such systems. Our finding is in line with research that finds that the level of work experience influences how information is perceived and information systems used. Future research can expand on this to disentangle relations among experience, job-levels, and required training to further understand determinants of IPA adoption with regard to user experience (Kalyuga et al., 2003; Mayer & Moreno, 2003).

Transparency is no end in itself

In their call for research, Engel et al. (2022) explicitly refer to a need for investigations on making decisions of IPA tools explainable to users to foster IPA use. In this vein, we can confirm the relevance of Transparency and Trust in the context of AI-based technologies as highlighted by Venkatesh (2022). Accordingly, we propose to integrate the constructs Trust and Transparency for acceptance research around IPA as well as related technologies as integral constructs in future research models.

We agree with research on explainability of AI in that the creation of Transparency over AI-related technology can facilitate Trust and therefore adoption. 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 Trust. Lacity et al. (2016) were able to derive comparable findings when interviewing senior executives in an RPA context. Supporting the positive effects of Trust, we identified a strong negative effect on Perceived Risk. A direct moderating effect of Experience between Trust and Perceived Risk suggests that the effect may increase with Experience.

Related research on explainability and adoption of AI-related technology has revealed that Trust can be improved through various measures, including implementing and communicating frameworks for trustworthy AI and developing organizational trust management (Thiebes et al., 2021). In particular, Transparency can be facilitated 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 states of software robots and including inputs and outputs (Holder et al., 2021). As our research shows, Transparency works through the Trust and Perceived Risk as well as Performance Expectancy relation. Hence, we posit it is insufficient to provide "explanations" that merely make things transparent by providing data and information but focus on user-centered explanations that provide clarity and understanding about decisions of IPA tools, such as for example predictions (Herm et al., 2023). In the context of IPA, this may be even more important than for decisional AI as the tasks of the AI involve not only decision-making but also task execution. Consequently, this work relation between human and IPA resembles a delegation situation rather than a software selection decision which makes bridging the information asymmetry between the two parties ever more important.

Limitations

Our research has some methodological and content-wise limitations to be considered when interpreting and using the results. In terms of methodology, the literature review and concept matrix creation have subjective components, such as the exclusion of publications. To mitigate this potential limitation, we strictly adhered to guidelines diffused in Information Systems (vom Brocke et al., 2009; i.e., vom Brocke et al., 2015; Webster & Watson, 2002). Moreover, there are limitations inherent to online studies as these do not enable to monitor participants directly. Prolific.com includes a live chat to answer immediate questions but cannot compensate for a lack of personal interaction. To ensure the quality of answers, we screened results for irregular execution times and also on the basis of attention checks.

Moreover, established, generic models like UTAUT provide only one structured approach to studying acceptance (Williams et al., 2009). We chose to use such a model because we are among the first to investigate IPA adoption on this scale. By doing so, we build on a large body of existing knowledge, comparable to many recent innovative contributions in Information Systems (e.g., Hooda et al., 2022; Misra et al., 2022; Wanner et al., 2022; Xu et al., 2024). At the same time, we create opportunities for future research to explore other approaches, such as purely qualitative, exploratory studies that are less restricted to long-established constructs. In this vein, we find novel approaches of assessing technology acceptance that are diffusing in Information Systems research. For example, Baird and Maruping (2021) emphasize the need of considering agency regarding the adoption of AI artifacts. Further, several researchers propose integrating theoretical notions on task-technology fit with TAM and UTAUT to explain variance in user adoption (e.g., Bouwman & van de Wijngaert, 2009; van Huy et al., 2024). While upcoming approaches like these seem promising also for the context of IPA, their relatively low level of diffusion reduces comparability. In terms of content-wise limitations, we find that 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 quiet quitting. Further, research has also shown that

constructs such as Social Influence and Perceived Risk can be dependent on the cultural background of the respondents (e.g., Bandyopadhyay & Fraccastoro, 2007; Verhage et al., 1990). The empirical survey was conducted in English only. Due to the inseparable link between language and culture, people from different cultural backgrounds may have been excluded (Jiang, 2000). This imperfection of the research (Williams et al., 2015) could lead to a bias in the results, leaving potential for future investigations.

Conclusion and future work

IPA leverages advantages of symbolic process automation with AI to automate complex business processes requiring decision-making capacities. Despite the economic pressure to take advantage of IPA and its potential competitive advantages, the adoption rate of IPA is comparatively low. To understand reasons and identify areas for action towards IPA adoption as considered explicitly necessary in IS research (Engel et al., 2022), we identified 13 determinants and created an extended UTAUT model (cf. Table 1). Providing normative knowledge with the UTAUT extension, we show influential relations between identified determinants for IPA adoption. In particular, we find that it is important to cultivate a positive attitude towards IPA, establish suitable facilitating conditions, especially mind user experience, and embrace the fact that transparency is no end in itself and does need to provide explainability of system behavior rather than "explanations" in terms of mere data and information. Our research entails two starting points for future research. First, further studies with a larger number of participants or with a focus on certain participant characteristics, such as culture, can further test robustness and contingencies of our developed model. Second, research can further extend the model with more determinants originating from practical applications, for example by conducting research based on case studies. As a bridge towards other design-oriented research, this research can be used to inform requirements engineering and the design of complex IPA building blocks such as data trust models where complex and flexible interactions with multiple parties exceed the boundaries of symbolic process automation.

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