Are Entrepreneurial Employees More Inclined to Accept Artificial Intelligence? An Extension of the UTAUT2

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Abstract

Albeit the increased use of artificial intelligence (AI) in organizations, the understanding of how employees perceive its introduction and which factors play a role in their usage intentions and behavior is still underdeveloped. This study draws on the UTAUT2 by Venkatesh et al. (2012) to investigate AI acceptance by employees in more detail. Structural equation modeling results of a survey with employees (N = 224) reveal that age, gender, experience, and attitude towards AI show partially moderating effects for the UTAUT2 measurements. We analyze how employees' entrepreneurial mindset influences their usage intention, as we expect entrepreneurially-minded individuals to perceive AI introduction differently. We find ambiguous results regarding entrepreneurial mindset as creativity, propensity to risk, and the perceived entrepreneurial benefits as well as attitude show moderating effects, both strengthening and weakening UTAUT2 relationships. This study contributes theoretical implications towards extending the UTAUT2 with moderators as well as practical implications for organizations.

Keywords: Unified Theory of Acceptance and Use of Technology 2, UTAUT2, entrepreneurial mindset, artificial intelligence, user acceptance

1. Introduction

Artificial Intelligence (AI) has become an increasingly important technology and it is revolutionizing the way businesses operate. Kaplan and Haenlein (2019) stated that when a system can interpret external data in the right way, learn from this data, and complete tasks by adapting dynamically, then it is based on AI. This definition has found appreciation in research as it combines the functionalities and capabilities of AI in a concise manner (Stahl et al., 2023). Therefore, we also use this definition as a basis for our study. Artificially intelligent systems have the potential to significantly enhance efficiency of organizations by automating routine and repetitive tasks, enabling data-driven decision-making, and creating new forms of business models (Townsend & Hunt, 2019).

Due to the increased usage of AI in organizations, research and practice are increasingly interested in understanding users' acceptance towards automated systems. When acceptance of AI is low, the actual usage and integration into organizational processes will not enable firms to be more effective, but rather slow down organizations in going forward (Kelly et al., 2023). Research has not yet developed a validated and established theoretical model which comprehensively addresses AI user acceptance. So far, research has focused on validating more established models that cover the usage of technology such as the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2; Venkatesh et al., 2012), which merges several different technology acceptance models, making it the most profound theory of this matter as established by previous research (Bawack & Desveaud, 2022). Therefore, this study uses the UTAUT2 by Venkatesh et al. (2012) and tries to extend it towards the acceptance of AI technologies. The need to extend the model in the context of AI acceptance stems from the fact that AI technologies heavily differ in nature compared to other technologies. Glikson and Woolley (2020) explain that AI differs in regard to other technologies in two distinct ways: First, AI is based on machine learning, which is mostly based on calculations that are not entirely understood by their programmers. Second, AI can make decisions while having the potential to achieve greater results than humans. Thus, employees develop different opinions about AI compared to other technologies which is why we understand the urgency to analyze AI acceptance in addition to more established technology acceptance.

The press and other media channels regularly report headlines about both advancements and downfalls of AI (Nader et al., 2022), ChatGPT being one prominent example for both sides of the coin (Rampton, 2023). When a company introduces AI to exploit the many advantages these systems offer, it is however not yet

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clear how employees react and specifically how they behave and use AI. Thereby, this study analyzes which factors play a role for the intention to use AI and for actual usage behavior based on the UTAUT2.

In addition, the employees' entrepreneurial mindset influences how they work and what they seek after in their daily working life (Kuratko et al., 2023). Entrepreneurially-minded individuals show characteristics of actual entrepreneurs, who are known to be more venturesome, creative, see mistakes as challenges to improve, and think that they have a high impact in changing their abilities (Gartner, 1990). Accordingly, they are more prone to try something new, take more risks, and are more adaptive and flexible in new and unknown scenarios (Kuratko et al., 2021). As the introduction of AI in companies results in a revolutionary new situation for employees, it is reasonable to believe that employees who show a high entrepreneurial mindset might tackle this challenge differently and more openly than other employees. Thus, in this study, we integrate employees' entrepreneurial mindset by investigating the additional variables creativity, perceived entrepreneurial benefits, propensity to risk, and entrepreneurial attitude as moderators of the effects included in the UTAUT2.

This study contributes to research in three significant ways, particularly in advancing theoretical development: First, we enhance the understanding of AI acceptance by applying and critically evaluating the UTAUT2 framework in an underdeveloped context—employee interaction with AI technologies. This allows us to refine the UTAUT2 model by validating some proposed drivers, while challenging others, offering a more nuanced perspective on its relevance in AI-related settings. Second, we highlight the entrepreneurial mindset as a key concept, expanding its understanding by demonstrating its influence on organizational operations, as established in prior research (Daspit et al., 2023; Kuratko et al., 2023). This contributes to a deeper understanding of how organizations can boost their innovative potential. Finally, we extend the UTAUT2 model by empirically validating entrepreneurial mindset as a moderator, showing that an employee's entrepreneurial mindset plays a crucial role in shaping AI usage intentions. This directly addresses the research gap identified by Townsend and Hunt (2019) and further enriches the theoretical dialogue on the intersection of entrepreneurship and AI acceptance.

2. Theoretical background and hypotheses development

2.1 Unified theory of acceptance and use of technology 2 (UTAUT2)

The importance of analyzing user's acceptance of technologies has heavily increased in the past years (Zhao et al., 2023). Venkatesh et al. (2003) saw the plethora of developed models for technology acceptance and brought them together in one overarching theory, the UTAUT, which Venkatesh et al. (2012) further developed to the UTAUT2. With the rise of AI over the past decades, user acceptance of AI has been particularly in focus as many organizations try to implement AI-based systems in their processes. So far, research has not yet developed a comprehensive, well-grounded and established theoretical model on user acceptance of AI. Hence, we use the already existing UTAUT2, covering user acceptance of technology in general, but also covering important factors relevant for AI usage. We exclude price value in our study as employees do not buy the AI themselves but rather the employer decided to introduce specific AI-based systems at the workplace and paid for it. Upadhyay et al. (2022) used elements of the UTAUT2 to analyze AI acceptance of entrepreneurs and found that performance expectancy, social influence, and hedonic motivation had a significant influence on the behavioral intention. Wu et al. (2022) investigated user behavior concerning AI-based learning management systems and showed that performance expectancy, effort expectancy, and social influence had an impact on the behavioral intention to use these systems. Further, Cao et al. (2021) make use of UTAUT2 variables to understand AI decision-making and find that performance expectancy, effort expectancy, and the attitude towards AI play an important role for the behavioral intention. These findings support the assumption that the UTAUT2 holds explanatory power for the investigation of AI acceptance and usage. As previous literature has already investigated the usage intention and behavior of AI by means of the UTAUT2, we do not include the first seven hypotheses that cover the independent variables of the model being performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, habit as well as mediating effects of the behavioral intention on use behavior. In our study, we focus on investigating UTAUT2 moderating effects as well as additional moderating effects of attitude towards AI.

Previous studies have identified that the so-called digital divide meaning the gap between individuals who have easier access to technologies and those who have not is still prevalent (Niehaves & Plattfaut, 2014). Oftentimes, older people are associated with the latter category as it is harder for them to grasp new technologies, because they did not grow up with them (Morris & Venkatesh, 2000). However, there exists also evidence that this digital divide seems to narrow down and that most older people just need other resources and instructions when being confronted with new technological tools (Araujo et al., 2020; Langer et al., 2022). Thus, we want to test how the effect of age as a moderator influences UTAUT2 variables as follows:

H1: Age moderates the relationships of (a) performance expectancy, (b) effort expectancy, (c) social influence, (d) facilitating conditions, (e) hedonic motivation, and (f) habit with behavioral intention as well as the relationship of (g) behavioral intention with use behavior.

The idea that women and men accept AI in distinct ways can be linked to prior research that examined the significant hurdles women face when entering the technology industry (Clegg & Trayhurn, 2000). Scholars also highlighted that men tend to exhibit greater technological proficiency (Goswami & Dutta, 2016). Nevertheless, these barriers seem to break down and the assigned social roles for men, women, and other genders are brought closer together (Del Carpio & Guadalupe, 2022). Therefore, it is questionable how and if gender is an appropriate moderator for the UTAUT2 in current times. However, we argue that thus far barriers still exist for women in technological industries as recently proposed by Schulenberg and colleagues (2023) and, hence, we posit as follows:

H2: Gender moderates the relationships of (a) performance expectancy, (b) effort expectancy, (c) social influence, (d) facilitating conditions, (e) hedonic motivation, and (f) habit with behavioral intention as well as the relationship of (g) behavioral intention with use behavior.

When being experienced with AI, it seems logical that the use of AI at the workplace is perceived differently than from people who have no or very little experience with AI. In this case, prior experience refers to the level of how often individuals have interacted with technology, in our case AI, in the past (Venkatesh et al., 2012). When users are exposed to a technological tool over a longer period of time, knowledge about how the tool operates is increasing as well as the confidence on how to interact with it (Chong et al., 2022). Therefore, these experiences can shape adoption patterns in a positive way. Previous studies have identified that experience can be viewed as an influential factor in the UTAUT2 when extending the model towards AI instead of technology acceptance (Kelly et al., 2023). However, these studies did not analyze the acceptance or usage of AI from the employee perspective, they rather focused on other user groups (e.g., teachers, public; Liu & Tao, 2022; Wang et al., 2021). Therefore, it is important to understand whether employees show similar cognitive and behavioral patterns regarding AI usage, hence, we hypothesize as follows:

H3: Experience moderates the relationships of (a) performance expectancy, (b) effort expectancy, (c) social influence, (d) facilitating conditions, (e) hedonic motivation, and (f) habit with behavioral intention as well as the relationship of (g) behavioral intention with use behavior.

As stated above, the topic of AI is currently highly discussed in the media and press both regarding its positive and negative aspects (Nader et al., 2022). Therefore, we posit that people in general have formed specific opinions and attitudes towards algorithm-based systems which in turn influence their behavioral intentions and usage with AI (Chowdhury et al., 2023). Previous literature has identified attitude towards AI as an important influence factor when looking at employee reactions towards AI (Schepman & Rodway, 2020). More specifically, employees who have a more positive attitude towards AI have shown to be more accepting of AI introduction for example in recruiting practices (Langer et al., 2022). In turn, we expect the employees' positive attitude towards AI to be a useful extension of the UTAUT2, especially for the integration of AI-related constructs in the model. Therefore, we integrate findings from previous literature, which state that attitudes towards technology are an important extension of the UTAUT2 model (Weichbroth et al., 2022) This leads to our next hypothesis:

H4: Attitude towards AI moderates the relationships of (a) performance expectancy, (b) effort expectancy, (c) social influence, (d) facilitating conditions, (e) hedonic motivation, and (f) habit with behavioral intention as well as the relationship of (g) behavioral intention with use behavior.

2.2 The intersection of entrepreneurial mindset and AI

Previous research defined the entrepreneurial mindset as a cognitive approach that enables individuals to create value by seizing opportunities, making decisions with limited information, and staying adaptable in uncertain, complex environments (Daspit et al., 2023). More specifically, Kuratko et al. (2021) divide the entrepreneurial mindset into three aspects: The cognitive aspect, the emotional aspect, and the behavioral aspect. The cognitive aspect summarizes the understanding that entrepreneurially-minded individuals have higher cognitive abilities to bring unconnected information together. We include the entrepreneurial mindset in this study by means of the variables of creativity and perceived entrepreneurial benefits as conceptualization of the cognitive aspect. Creative employees find new ways to achieve goals and objectives (Zhou & Gorge, 2001) and, therefore, creativity goes along with the understanding of Kuratko et al.'s (2021) cognitive adaptability which is included under the cognitive aspect in entrepreneurial mindset. Cognitive adaptability can be characterized by the skill to be highly dynamic and flexible in risky environments (Kuratko et al., 2021). Previous studies have established that creativity influences and fosters technology usage in different ways (Jackson et al., 2012), hence, we want to understand if the findings hold true for AI-based systems as well. Therefore, we assume that creative employees, that is, employees with a higher entrepreneurial mindset, have different drivers for intending to use AI than less creative employees, that is, employees with a lower entrepreneurial mindset. Accordingly, our next hypothesis reads as follows:

H5: Creativity moderates the relationships between (a) performance expectancy, (b) effort expectancy, (c) social influence, (d) facilitating conditions, (e) hedonic motivation, (f) habit, and behavioral intention.

In addition, previous literature has confirmed that individuals who perceive an entrepreneurial activity as beneficial have a higher entrepreneurial mindset (Shepherd et al., 2000). Similarly to creativity, when someone perceives an entrepreneurial activity as positive, they are more likely to deal well with stress and like to tackle challenges more often, all being characteristics that Kuratko et al. (2021) subsume in their understanding of cognitive adaptability. Thus, we introduce the perceived benefits of an entrepreneurial activity as an additional driver of the cognitive aspect in the entrepreneurial mindset and hypothesize that employees who view entrepreneurial activities as beneficial use AI differently. Hence, we hypothesize:

H6: Perceived entrepreneurial benefits moderate the relationships between (a) performance expectancy, (b) effort expectancy, (c) social influence, (d) facilitating conditions, (e) hedonic motivation, (f) habit, and behavioral intention.

Kuratko et al. (2021) also include the emotional aspect into entrepreneurial mindset, which means that entrepreneurially-minded people can also process their emotions in a way so that they take the positive even out of challenging times. In regards to the behavioral aspect, entrepreneurial mindset stands for actions so that individuals are more likely to put their thoughts faster into action. As the behavioral aspect is already integrated in our research model in terms of behavioral intention and actual usage behavior regarding AI, we disregard it for our moderator conceptualization in terms of entrepreneurial mindset. We conceptualize propensity to risk as well as entrepreneurial attitude as representation of the emotional aspect. When being faced with challenges, someone with risk-taking characteristics has the emotional ability to act faster than others (Yip & Côté, 2013). Kuratko et al. (2021) themselves categorize the confrontation with risk under the umbrella of the emotional aspect, hence, we use it as a conceptualization for the emotional component of entrepreneurial mindset. Hansen et al. (2018) have shown that risk-taking is an influential antecedent in technology usage. We thereby want to extend previous results to the AI context and hypothesize:

H7: Propensity to risk moderates the relationships between (a) performance expectancy, (b) effort expectancy, (c) social influence, (d) facilitating conditions, (e) hedonic motivation, (f) habit, and behavioral intention.

When being faced with uncertainty, entrepreneurially-minded individuals are more resilient to overcome unknown situations, which is understood as having a high entrepreneurial attitude (Liñán & Chen, 2009). As attitudes and emotions are closely related, we use the entrepreneurial attitude as further conceptualization of the emotional aspect in the entrepreneurial mindset. Using AI is also an unknown territory at first, which is why we expect entrepreneurially-minded employees to approach AI usage differently than other employees, leading to the next hypothesis:

H8: Entrepreneurial attitude moderates the relationships between (a) performance expectancy, (b) effort expectancy, (c) social influence, (d) facilitating conditions, (e) hedonic motivation, (f) habit, and behavioral intention.

We present our research model in Figure 1.

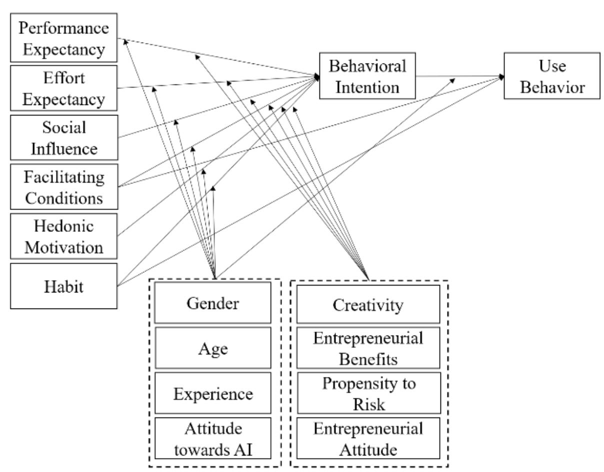

Figure 1. Hypothetical research model.

3. Methodology

3.1 Design and participants

We conducted a pre-test with nine participants to ensure the comprehensibility of the survey questions. With their feedback, we adjusted the formulation of some of the items to increase the comprehensibility of our survey. Together with Clickworker, an ISO 27001:2017 certified online sample provider, we distributed the questionnaire. In total, we acquired 273 participant responses, meeting our study requirements (that is, to be over the age of 18, to be currently employed and to have used AI before or currently at work). We removed 17 duplicates and ten participants who did not pass the attention checks. After an anomaly and outlier check, we eliminated another 22 respondent answers. Our final sample consists of 224 eligible participants, of which 34.8 percent were female, 64.7 percent male and 0.4 percent diverse. The mean age of the sample was 38.61 years (*SD* = 10.99).

3.2 Measurements

All survey items were measured on a 7-point Likert scale, where 1 corresponded to “strongly agree” and 7 to “strongly disagree”. Further, we implemented three attention checks due to the length of the survey.

UTAUT2 measurements. Since the survey was conducted in the DACH region, we translated all items into German, using Harborth and Pape’s (2018) validated German translation for the UTAUT2 items. The remaining items were translated from English to German and validated by native speakers. Further, we adapted the original UTAUT2-items from Venkatesh et al. (2012) to fit our context. For this, we exchanged “mobile internet” in all items with “artificial intelligence” and added “in my company” afterwards. This goes in line with the procedure of previous research (Upadhyay et al., 2022).

Moderation measurements. We conceptualized the moderator experience from the UTAUT2 by asking the participants how often they have already worked with AI at the workplace with a 7-point Likert scale ranging from “very often” to “very seldom”. We conceptualized the entrepreneurial mindset with creativity, the perceived benefits that would arise from entrepreneurial activities, propensity to risk, and entrepreneurial attitude. Creativity was measured with eleven items from Zhou and George’s (2001) scale. We introduced perceived entrepreneurial benefits with seven items (Rodrigues et al., 2023; Shepherd et al., 2000) as well as all five items of the Entrepreneurial Attitude Orientation scale (Liñán & Chen, 2009). We measured propensity to risk with 14 items from the General Risk Propensity Scale (GRiPS) (Zhang et al., 2019). Furthermore, for the attitude someone has towards AI, we used the General Attitudes towards Artificial Intelligence Scale (GAAIS) by Schepman and Rodway (2020).

3.3 Analytical procedures

We used structural equation modeling (SEM) to analyze our research model. Such an analytical approach is appropriate when having a sample size larger than $N > 200$. The first stage in the SEM analysis was to conduct a confirmatory factor analysis (CFA) of all latent variables in SPSS AMOS to investigate the standardized factor loadings. Items with factor loadings below 0.70 should be excluded. We first calculated the CFA with a model that included all items (model fit: $\chi^2 = 116.27$, $p = .053$, RMSEA = .057, CFI = 1.00).

Table 1. Descriptive statistics and correlations.

	Variable	M	SD	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	PE	5.25	1.12	*(.91)*														
2	EE	4.96	1.09	.59**	*(.88)*													
3	SI	4.23	1.29	.42**	.32**	(.92)												
4	FC	4.97	1.29	.52**	.68**	.29**												
5	HM	4.75	1.22	.51**	.43**	.37**	.33**	*(.88)*										
6	HA	4.43	1.48	.52**	.54**	.47**	.47**	.40**										
7	Age	38.44	10.85	.05	.14*	.02	.21**	-.14*	.01									
8	Gender	1.41	.51	-.05	-.02	-.01	-.05	.02	-.07	-.09								
9	Exp.	4.51	1.31	.42**	.44**	.29**	.46**	.32**	.53**	.02	-.04							
10	GAAIS	4.68	.71	.42**	.27**	.24**	.20**	.27**	.24**	-.02	-.08	.14*	*(.70)*					
11	Attitude	4.51	1.45	.19**	.26**	.08	.21**	.30**	.14*	-.01	.00	.18**	.27**	*(.94)*				
12	Benefits	4.64	1.35	.22**	.35**	.15*	.30**	.27**	.24**	.08	.00	.23**	.28**	.70**	*(.83)*			
13	Prop. Risk	4.02	.90	.15*	.25**	.26**	.16*	.25**	.22**	-.17**	-.15	.20**	.23**	.29**	.32**	*(.73)*		
14	Creativity	5.11	.98	.29**	.36**	.11	.39**	.25**	.24**	.10	.05	.25**	.43**	.44**	.52**	.25**	*(.93)*	
15	BI	5.30	1.20	.70**	.63**	.36**	.54**	.48**	.55**	.07	-.04	.40**	.35**	.15*	.23**	.19**	.29**	*(.91)*
16	UB	5.45	1.99	.35**	.39**	.25**	.38**	.26**	.44**	-.03	.07	.64**	.06	.08	.13*	.11	.15*	.38**

Note. PE = performance expectancy, EE = effort expectancy, SI = social influence, FC = facilitating conditions, HM = hedonic motivation, HA = habit, Exp. = experience, GAAIS = General Attitudes towards Artificial Intelligence, Attitude = entrepreneurial attitude, Benefits = entrepreneurial benefits, Prop. Risk = propensity to risk, BI = behavioral intention, UB = use behavior, *M* = mean, *SD* = standard deviation. Cronbach’s Alpha is reported on the diagonal axis. $N = 224$, * $p < .05$, ** $p < .01$.

We excluded 25 items that had a value below 0.70 from our analyses, increasing the model fit ($\chi^2 = 67.91$, $p = .200$, RMSEA = .026, CFI = 1.00). A fitting model should generally have a non-significant chi-square value, a comparative fit index (CFI) greater than 0.95, and a root mean square error (RMSEA) value less than 0.06 (Bollen, 1989; Browne & Cudeck, 1992). These conditions were met in our model, hence, allowing as to continue with our analyses.

After the CFA, we created the variables with the fitting items and estimated their Cronbach's Alpha as well as the discriminant validity. All Cronbach's Alphas of the scales were above the widely accepted threshold of $\alpha = 0.70$. For analysis of the moderation effect, we calculated the interaction terms for the moderators by mean centering the variables and multiplying them with the independent UTAUT2 variables accordingly.

4. Results

4.1 Descriptive statistics

All means, standard deviations, and correlations are depicted in Table 1. The correlations ranged from small to high, while never exceeding .70, which would indicate multicollinearity. Therefore, we were able to go further with our analysis.

4.2 SEM results

Table 2 presents our SEM results including all results for the moderating effects.

Table 2. Structural equation modeling results.

Variable	*B*	*SE*	*β*	*p*	Hypotheses
PE → BI	.39***	.06	.36	< .001	
EE → BI	.21***	.06	.20	< .001	
SI → BI	.01	.04	.01	.863	
FC → BI	.00	.05	.00	.989	
FC → UB	.02	.11	.01	.839	
HM → BI	.07	.05	.08	.148	
HT → BI	.00	.04	.01	.929	
HT → UB	.05	.10	.04	.602	
BI → UB	.09	.15	.05	.531	
Moderation effects					
Age					
PE → BI	.03	.07	.02	.681	Reject H1a
EE → BI	.16*	.08	.14	.031	Confirm H1b
SI → BI	.08	.05	.07	.113	Reject H1c
FC → BI	-.19**	.07	-.16	.007	Confirm H1d
HM → BI	.13*	.06	.11	.022	Confirm H1e
HT → BI	-.18**	.06	-.14	.003	Confirm H1f
Age → UB	.02	.10	.01	.828	Reject H1g
Gender					
PE → BI	-.02	.06	-.02	.714	Reject H2a
EE → BI	-.05	.06	-.04	.429	Reject H2b
SI → BI	-.17**	.06	-.15	.002	Confirm H2c
FC → BI	.06	.07	.05	.398	Reject H2d
HM → BI	.08	.06	.07	.180	Reject H2e
HT → BI	.04	.06	.04	.471	Reject H2f
Gender → UB	.00	.11	.00	.970	Reject H2g
Experience					
PE → BI	.00	.06	.00	.976	Reject H3a
EE → BI	.06	.07	.05	.408	Reject H3b
SI → BI	-.15*	.06	-.15	.011	Confirm H3c
FC → BI	-.05	.06	-.05	.408	Reject H3d
HM → BI	.01	.06	.01	.826	Reject H3e
HT → BI	.07	.06	07	.283	Reject H3f
Experien-ce → UB	.20*	.10	.12	.042	Confirm H3g
General Attitudes towards Artificial Intelligence Scale					
PE → BI	-.04	.07	-.05	.574	Reject H4a
EE → BI	-.28***	.07	-.28	< .001	Confirm H4b
SI → BI	-.13*	.07	-.12	.049	Confirm H4c
FC → BI	.13	.07	.11	.075	Reject H4d
HM → BI	-.06	.06	-.07	.285	Reject H4e
HT → BI	.25***	.07	.26	< .001	Confirm H4f
GAAIS → UB	-.13	.09	-.09	.181	Reject H4g
Creativity					
PE → BI	.05	.07	.05	.483	Reject H5a
EE → BI	-.07	.07	-.06	.292	Reject H5b
SI → BI	.16*	.07	.15	.023	Confirm H5c
FC → BI	-.20**	.07	-.18	.003	Confirm H5d
HM → BI	-.06	.07	-.05	.384	Reject H5e
HT → BI	.02	.07	.02	.739	Reject H5f
Entrepreneurial Benefits					
PE → BI	.22*	.11	.19	.036	Confirm H6a
EE → BI	.28*	.11	.27	.012	Confirm H6b
SI → BI	.12	.09	.14	.161	Reject H6c
FC → BI	-.26**	.10	-.05	.008	Confirm H6d
HM → BI	-.05	.08	-.05	.493	Reject H6e
HT → BI	-.28*	.11	-.28	.011	Confirm H6f
Propensity to risk					
PE → BI	-.09	.07	-.07	.198	Reject H7a
EE → BI	.13	.09	.11	.156	Reject H7b
SI → BI	.15*	.06	.14	.012	Confirm H7c
FC → BI	-.08	.07	-.08	.226	Reject H7d
HM → BI	-.03	.05	-.02	.605	Reject H7e
HT → BI	.08	.06	.07	.164	Reject H7f
Entrepreneurial attitude					
PE → BI	-.11	.10	-.10	.277	Reject H8a
EE → BI	-.41***	.13	-.37	<.001	Confirm H8b
SI → BI	-.09	.09	-.09	.316	Reject H8c
FC → BI	.14	.10	.11	.186	Reject H8d
HM → BI	.06	.08	.06	.428	Reject H8e
HT → BI	.15	.11	.14	.181	Reject H8f

Note. *B* = unstandardized effect, *SE* = standard error, *β* = standardized effect, PE = Performance expectancy, EE = Effort expectancy, SI = Social influence, FC = facilitating conditions, HM = Hedonic motivation, HT = Habit, PR = Propensity to risk, CR = Creativity, EB = Entrepreneurial benefits, EA = Entrepreneurial attitude, GAAIS = General Attitudes towards Artificial Intelligence Scale, BI = Behavioral intention, UB = Usage behavior; $N = 224$, * $p < .05$, ** $p < .01$, *** $p < .001$.

In terms of age, we can confirm the moderating effect of age between effort expectancy and behavioral intention ($\beta = 0.14$, $p = .031$), facilitating conditions and behavioral intention ($\beta = -0.16$, $p = .007$), hedonic motivation and behavioral intention ($\beta = 0.11$, $p = .022$) as well as habit and behavioral intention

(β = -0.14, p = .003), resulting in confirming H1b, H1d, H1e, and H1f. For gender, we can confirm H2c in terms of moderating effects of gender for the relationship between social influence and behavioral intention (β = -0.15, p = .002). We find that experience moderates the relationship between social influence and behavioral intention (β = -0.15, p = .011), confirming H3c. The results show that the attitude towards AI moderates the relationship between effort expectancy and behavioral intention (β = -0.28, p < .001), social influence and behavioral intention (β = -0.12, p = .049), and habit and behavioral intention (β = 0.26, p < .001), hence, confirming H4b, H4c, and H4f. Furthermore, we find that the paths between social influence and behavioral intention (β = 0.15, p = .023) as well as facilitating conditions and behavioral intention (β = -0.18, p = .003) are moderated by creativity, confirming H5c and H5d. Perceived entrepreneurial benefits have moderating effects for the relationships of performance expectancy and behavioral intention (β = 0.11, p = .036), effort expectancy and behavioral intention (β = 0.27, p = .012), facilitating conditions and behavioral intention (β = -0.05, p = .008) as well as habit and behavioral intention (β = -0.28, p = .011). Thus, we can confirm H6a, H6b, H6d, and H6f. Finally, our results show that propensity to risk moderates the relationship between social influence and behavioral intention (β = 0.14, p = .012) and entrepreneurial attitude shows moderating effects of the path between effort expectancy and behavioral intention (β = -0.37, p < .001). All of the other hypotheses needed to be rejected due to a p-value of above .050.

5. Discussion

The aim of this study is to extend the UTAUT2 to employees' acceptance of AI with moderating variables about their entrepreneurial mindset, that is their creativity, perceived entrepreneurial benefits, propensity to risk, and entrepreneurial attitude. Further, our goal is to test moderating effects of age, gender, experience, and attitude towards AI to better understand the UTAUT2 itself and trying to adapt it to the AI context. When investigating the results of age, we see that older employees focus on effort expectancy and hedonic motivation in their behavioral intention, whereas we find opposing effects for facilitating conditions and habit with behavioral intention. In addition, gender weakens the relationship between social influence and behavioral intention. The results depict that the attitude towards AI has negative effects for the relationship between effort expectancy and behavioral intention as well as social influence and behavioral intention, but a positive relationship between habit and behavioral intention. Creativity strengthens the relationship between social influence and behavioral intention, however, it weakens the relationship between facilitating conditions and behavioral intention. When employees perceive entrepreneurial activities to be beneficial, they have higher performance expectancy and effort expectancy towards their behavioral intention, but lower facilitating conditions and habit towards their behavioral intention.

In terms of the moderator age, we find that older employees have higher expectations towards the usability of an AI system (effort expectancy) as well as towards the need to feel more enjoyment when interacting with AI to increase behavioral intention (hedonic motivation). Conversely, older employees rely less on the facilitating conditions the organization provides for AI usage and do not prioritize building a habit when interacting with AI to increase behavioral intention. These findings show that older employees might need to be treated differently in terms of AI introduction compared to younger ones, as their focus relies on different factors that increase behavioral intention. In addition, our findings show that the digital divide still persists to some degree, rather than giving support that the barriers are reduced (Araujo et al., 2020).

We find that gender negatively moderates the relationship between social influence and behavioral intention, meaning women are more likely than men to intend to use AI when experiencing social pressure. This aligns with Venkatesh et al. (2003) and may be because women typically rely more on their social network for advice (Kimbrough et al., 2013). Despite claims that gender differences in technology usage are narrowing, our results show these differences persist, specifically regarding social influence.

We further find that a higher positive attitude towards AI leads to more importance of habit in the behavioral intention to use AI. Effort expectancy and social influence play a less important role in shaping the behavioral intention. Therefore, someone who feels positive about AI does not feel pressured to use AI when their environment thinks otherwise (Araujo et al., 2020).

Furthermore, our results depict that creative employees rely less on facilitating conditions when intending to use AI. Creative individuals are very good at finding their own ways and solutions for problems which is why it makes sense that they need less resources from their organization (Mumford, 2000). Interestingly, creative employees rely more on social influence in their behavioral intention compared to less creative ones.

Additionally, we show that the perceived entrepreneurial benefits positively moderate the relationship between performance expectancy and behavioral intention as well as effort expectancy and behavioral intention, enhancing the findings from Upadhyay et al. (2022), who found significant relationships between these variables for entrepreneurs. Interestingly, the results showed that the relationships between facilitating conditions and behavioral intention as well as habit and behavioral intention are negatively moderated by the perceived entrepreneurial benefits. This means that employees who perceive an entrepreneurial endeavor as not beneficial for them, need less resources from the organization employing AI and the organization needs to put higher efforts in creating a habit for them.

In summary, we expand findings from previous research as we show important factors for AI adoption in entrepreneurially-minded employees, while also shedding light onto less impactful factors, such as hedonic motivation or habit.

5.1 Theoretical implications

We extend theory in four major ways: First, we expand the UTAUT2 for AI acceptance and usage by employees. As the intricacies of AI adoption are still underdeveloped, we offer insights on how businesses can increase AI acceptance: For example, increasing employees' performance expectancy and decreasing their effort expectancy can lead to increasing employees' behavioral intention to use AI.

Second, we found that age has moderating effects despite the current debate that moderating effects of age are diminishing (Araujo et al., 2020). However, as we investigate the influential factors of the UTAUT2 together with age, we show how intricate the impact of age regarding AI acceptance looks like, and that age does not impact all relations between UTAUT2 measures and behavioral intention. Future studies could elaborate which other determinants play a role when assessing acceptance and use behavior for varying age groups.

Third, we showed that the attitude towards AI plays a moderating role for the usage intention of employees and, thus, should be integrated as a construct in future research that deals with understanding AI acceptance. Previous research has rather integrated concepts such as AI familiarity (Horowitz et al., 2023) as a potential influence on AI usage. However, these constructs neglect which emotions and feelings about AI employees hold and how they influence AI adoption.

Lastly, we found that the entrepreneurial mindset moderates the relationship between UTAUT2 constructs and behavioral intention to use AI, both strengthening and weakening these relationships. This highlights the underexplored intersection of entrepreneurship and AI usage.

5.2 Practical implications

We gather three important practical implications from our findings: First, we emphasize that organizations should tailor AI introduction based on age, as younger and older employees differ in their AI adoption intentions. For younger employees, building habits to foster long-term acceptance is crucial. Research shows that increased expertise and familiarity with AI enhance perceptions and usage behavior, reinforcing this approach (Horowitz et al., 2023).

Second, companies should consider that an inherently more positive attitude towards AI leads to habit being more important on the employees' intention to use AI. Hence, organizations could introduce trainings on how AI can be integrated into everyday tasks to increase habitual usage.

Lastly, our results indicate that an entrepreneurial mindset affects employees' intentions to use AI. We recommend that businesses assess their employees' entrepreneurial mindset to tailor AI introduction strategies. For example, providing additional resources to employees with a lower entrepreneurial mindset—those less creative, less risk-taking, or less inclined toward entrepreneurial activities—could boost AI adoption. Employees with a strong entrepreneurial mindset could serve as mentors to support those with a lower mindset.

5.3 Limitations and future research

Despite following all important guidelines regarding survey design, our study is limited in some capacity. The UTAUT2 covers a range of possible influential factors regarding usage intention and behavior of technologies. However, there might be other factors impacting these variables which we thereby did not address. Further studies could elaborate on the UTAUT2 in an AI context for a longer time period, using multiple measurement times to understand how AI acceptance might change over time, that is, with increased usage.

Our sample consisted of employees from the DACH region, which may have unique characteristics regarding AI acceptance. Since AI reactions vary across cultures (Mahmud et al., 2022), results could differ in other regions. Future studies should explore

AI acceptance cross-culturally to better understand the applicability of UTAUT2 in differing cultural settings.

Also, the UTAUT2's survey design is limited by relying on employees' subjective responses to a few questions. Future studies could explore AI acceptance in experimental settings for more realistic insights. However, this will require developing a theoretical model that goes beyond survey-based research.

Lastly, one future research endeavor might be related to both positive and negative moderating effects of entrepreneurial mindset on the relations in the context of the UTAUT2: For example, regarding the findings that creativity negatively moderates the relationship between facilitating conditions and behavioral intention and that propensity to risk positively moderates the relationship between social influence and behavioral intention, future studies could investigate if these effects are even more pronounced particularly in new ventures that often attract creative and risk-affine employees.

6. Conclusion

This study used the UTAUT2 model (Venkatesh et al., 2012) to investigate AI user acceptance, focusing on moderating effects between UTAUT2 variables, behavioral intentions, and usage behavior among employees using AI at work. We also explored how the entrepreneurial mindset influences AI interaction, hypothesizing that entrepreneurially-minded individuals engage differently with AI. SEM results revealed that age, gender, and attitude towards AI moderate behavioral intention. In addition, while an entrepreneurial mindset can aid AI acceptance in some aspects, it may hinder it in others. These insights can help organizations tailor AI strategies based on age, gender, AI attitudes, and entrepreneurial mindset to enhance behavioral intention and usage behavior.

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