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Beyond sufficiency: Necessary conditions for employees' intention to use personalized learning systems

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A B S T R A C T

Personalized learning systems offer tailored educational resources to individual learners, promising increased efficiency and engagement in workplace learning. While prior research has identified drivers of employees' intention to use such technology from a sufficiency perspective, less is known about necessary conditions. Building on a previously published study that applied structural equation modeling, this paper reanalyzes the data of 331 employees by means of necessary condition analyses (NCAs).

Thereby, the conventional probabilistic sufficiency perspective ('X produces Y') is supplemented by a necessity perspective ('X enables Y'). Utilizing the emerging NCA method uncovers essential enablers, meaning the behavioral intention typically does not occur in their absence. Thus, the present study expands previous findings on technology adoption through a necessity lens. To gain a more nuanced view, NCAs are conducted across subgroups (based on UTAUT2 moderators) to identify potential differences.

The findings reveal that the two most prominent factors in technology adoption research, namely performance expectancy ($d = 0.12$) and effort expectancy ($d = 0.17$), are necessary for employees' usage intention. Moreover, a lack of trustworthiness hinders performance expectancy ($d = 0.13$) and, subsequently, the intention to use. These novel insights contribute to theory development and inform practitioners who aim to implement personalized learning systems.

1. Introduction

Organizations increasingly recognize the importance of continuous learning as a strategic asset to foster innovation, retain talent, and adapt to dynamic environments. However, as Chen [1] noted, "no fixed learning paths will be appropriate for all learners" (p. 787). Personalized learning systems have emerged as a promising way to tailor content, path, pace, and instructional support to individual preferences, knowledge levels, and needs [2,3]. By improving the effectiveness and efficiency of training activities, such systems aim to enhance learning outcomes, engagement, and organizational performance [4,5].

The idea of tailoring electronic learning resources to individuals is not new [6] but is gaining momentum thanks to recent technological advances [7]. For example, with the rapid development of Generative Artificial Intelligence (GenAI), the potential for personalization is expanding rapidly [8]. GenAI-enhanced systems are not limited to static content selection but can dynamically generate context-specific explanations, provide tailored feedback, adjust task difficulty, and suggest learning paths based on real-time user input [7,9]. As a result, GenAI paves the way "from generic offerings to a personalized, interactive journey, addressing specific skills gaps" ([4], p. 48).

Despite these technological advancements, successful implementation depends on users' willingness to engage with these systems. Theoretical models of technology acceptance, such as the widely recognized Unified Theory of Acceptance and Use of Technology (2) (UTAUT(2); [10]), have been used to investigate factors that might influence employees' behavioral intention to adopt e-learning (e.g., [11–13]). In the specific field of personalized learning systems, prior research identified performance expectancy, hedonic motivation, and technology trustworthiness as drivers in shaping employees' intentions [14].

While these findings offer valuable insights from a *probabilistic sufficiency perspective* [15], one crucial issue remains open: *To what extent are the UTAUT2 constructs necessary conditions for employees' intention to use personalized learning systems?* Unlike most previous studies in the field of technology adoption, this question sheds light on causality from a *necessity perspective*. Examining employees' intentions through a necessity lens is relevant for both research and practice: doing so helps to refine theories, as necessary conditions should be incorporated [16].

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Otherwise, “there is a risk of erroneous predictions as the outcome cannot exist if the condition is absent” ([17], p. 36). For instance, it is conceivable that effort expectancy (also referred to as 'ease of use') is necessary but not sufficient for usage intentions to arise [18]. However, theories seldom contain statements about necessity [19].

Complementing previous findings based on sufficiency logic with insights based on necessity logic helps to avoid hasty conclusions [20], highlighting the theoretical and practical relevance of this study. Additionally, practitioners benefit from tangible guidance regarding conditions that must be present to achieve a desired outcome (e.g., based on bottleneck tables that illustrate necessity in degree; [21]).

To address the question raised above and to ensure theory-method fit, multiple Necessary Condition Analyses (NCAs) are conducted. The NCA method encompasses a specific causal logic as well as an appropriate data analysis technique [19]. This method is gaining increasing popularity [22], presumably due to its focus on a neglected causal perspective, the user-friendly R package [23], and well-written guidelines for good NCA practice (e.g., [19,22]). It enables investigating whether the UTAUT determinants are prerequisites for behavioral intention. In other words, such necessary conditions “must be present for achieving an outcome” ([21], p. 10).

Inspired by Dul et al. [17], who encourage the reuse of existing data to investigate necessity, the present study builds on existing data used by Schlagheck & Schewe [14]. They analyzed data from 331 German employees through a sufficiency lens by means of structural equation modeling and multi-group analyses. That dataset fits perfectly with the aim of the present study. After all, they examined employees’ intention to use personalized learning systems based on UTAUT2. Besides, using the same sample improves comparability with their sufficiency-based findings. To come up with even more targeted implementation strategies, this study additionally explores whether necessity effects vary across subgroups based on UTAUT2 moderators (age, gender, and experience).

To sum up, the present study applies NCA to determine which user beliefs are indispensable for forming an intention to use personalized learning systems. Combining a novel analytical perspective with practical implications for technology-enhanced learning adoption contributes to the evolving discourse on learning systems in the era of AI.

2. Theoretical background

Learning applications rank among the most promising areas of technology usage [24]. In particular, scholars highlight the transformative potential of personalized learning systems, justified by the adaptability of “the what and how of teaching and learning” ([25], p. 2). Such tailoring to learners’ individual needs is fostered by information and communication technology [25,26]. Specifically, foundational AI models facilitate personalized learning support and lay the foundation for technology-enhanced complex and domain-specific interactions [7]. Along with presumably higher learning outcomes [5], the advantages of personalized learning systems include real-time data processing [12], the identification of learning deficiencies [27], a reduction of instructors’ workload [26], round-the-clock availability [7], and geographical flexibility [24]. At the same time, potential downsides such as inaccurate information and over-reliance on AI, as well as feelings of constant monitoring and pressure, should be kept in mind [27–29].

In order to exploit the numerous advantages of personalized learning systems, technology acceptance among the potential user group is crucial [26]. Therefore, the present study builds on UTAUT2, which contains antecedents of behavioral intention and use behavior. The well-known UTAUT model incorporates constructs from previous models in the field of technology acceptance, such as perceived usefulness and perceived ease of use from the Technology Acceptance Model (TAM). These are termed performance expectancy and effort expectancy in UTAUT and are the most dominant constructs [30]. Further antecedents include social influence and facilitating conditions [31]. The more comprehensive UTAUT2 model additionally includes hedonic motivation, price value, and habit [10].

While e-learning belongs to the areas in which UTAUT is mainly used [32], empirical studies specifically addressing personalized learning systems are rare [33]. Given that these systems differ from traditional e-learning, it is crucial to take their specific nature into account. For instance, the more intense processing of sensitive data, such as individual learning progress, might raise concerns about privacy and surveillance [27].

In the context of personalized learning systems, previous research using structural equation modeling found that performance expectancy, hedonic motivation, and technology trustworthiness (mediated through performance expectancy) significantly influence employees’ intentions to use them [14]. Others identified performance expectancy, facilitating conditions, and social influence as factors affecting students’ intentions to use digital learning personalization [34]. Likewise, Panjaburee et al. [35] found a positive effect of usefulness but also of perceived ease of use. Notwithstanding these mixed findings, the literature lacks incorporation of necessity logic when analyzing the adoption of personalized learning systems.

There is a growing body of literature investigating UTAUT relationships through a necessity lens, with inconclusive results highlighting the need to consider the specific context. For instance, in the field of virtual influencers, Shao [36] found the largest necessity effect for social influence but a practically negligible effect for performance expectancy. In contrast, Hasselwander [37], who examined transport super apps, found no necessity effect for social influence, and Xiao et al. [38], who investigated driver assistance systems, revealed a large necessity effect of performance expectancy. Contrary to expectations, neither performance expectancy nor effort expectancy was necessary for the intention to use travel apps in the study by Tiwari et al. [39].

The present study transfers necessity logic to the field of personalized learning systems. To better compare the NCA results with Schlagheck & Schewe’s [14] findings, their research model is adopted (see Fig. 1). However, the arrows are now interpreted as 'is necessary' rather than 'is sufficient.' Consequently, the hypotheses derived below address the issue of “what will not occur in almost every case if a necessary condition is absent” (necessity logic; [15], p. 1) instead of “what will happen on average in a group of cases” (sufficiency logic; [15], p. 1). Three UTAUT2 constructs are not included in the model, namely price value, habit, and use behavior. This is because Schlagheck & Schewe [14] excluded them with justification, and there is no data available. Notwithstanding, they recognized the relevance of trustworthiness and, therefore, incorporated it into the model.

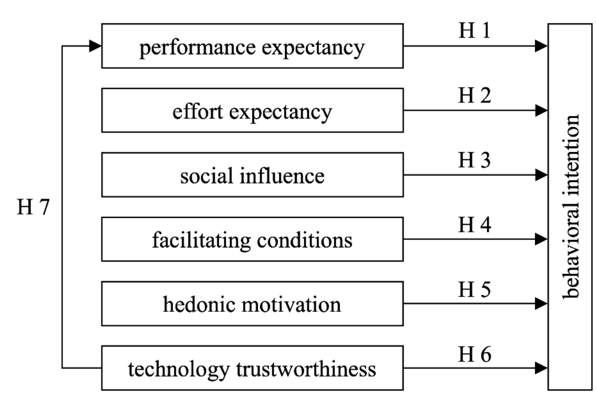

Fig. 1. The hypothesized model (own illustration based on [14]).
Note. H = necessity hypothesis.

3. Hypotheses development

3.1. Performance expectancy

Performance expectancy captures "the degree to which an individual believes that using the system will help him or her to attain gains in job performance" ([31], p. 447), also known as 'perceived usefulness,' which is the term used in the TAM. Following studies about e-learning acceptance [11,40] and in line with Schlagheck & Schewe [14], the focus here is on learning performance instead of job performance in general. Performance expectancy was found to affect behavioral intention positively [14,40] and is often the strongest UTAUT predictor for behavioral intention [32].

However, the question arises as to what extent this construct is even necessary for behavioral intention to occur. In fields other than personalized learning, performance expectancy was already found to be necessary for usage intention. For instance, Nguyen et al. [41] investigated mHealth technology adoption and found the largest necessity effect for perceived usefulness. NCA findings by Kayser & Gradtke [16] underline the importance of perceived utility with regard to ChatGPT. Likewise, usefulness is identified as a must-have factor for behavioral intention in the context of AI-generated content [42], customer-service robots [43], medicine vending machines [44], the mobile sharing economy [45], and mobile payment [46]. If a personalized learning system is not perceived as useful at all, employees presumably decline to use it (as long as the usage is not compulsory). Ultimately, these systems serve to enhance learning. If that is not the case, it would be more convenient to stick with established learning systems.

Hypothesis 1. *Performance expectancy is necessary for the intention to use personalized learning systems.*

3.2. Effort expectancy

Effort expectancy denotes "the degree of ease associated with the use of the system" ([31], p. 450). The corresponding term used in the TAM, namely 'perceived ease of use,' sounds more intuitive. After all, higher levels on the corresponding scale reflect less effort needed to use technology [47]. In other words, a high effort expectancy is aimed for (which also holds for the other UTAUT constructs). According to Schlagheck & Schewe's [14] sufficiency-based analysis, effort expectancy has no significant effect on behavioral intention.

Richter et al. [18] supplemented a sufficiency-based analysis with NCAs and found effort expectancy to be necessary but not sufficient in the context of e-book reader adoption. The same applies to Kopplin et al. [47], who studied matchmaking tools in coworking spaces. Further studies beyond learning technologies identified effort expectancy as a necessary condition for behavioral intention [43,48–51]. Similar findings in the context of personalized learning systems are conceivable, which would stress the importance of integrating necessity logic to avoid misleading conclusions [20]. Although employees might tolerate some complexity, a certain level of effort expectancy is likely required even to consider using a personalized learning system. If a system is perceived as overly difficult to navigate, the usage intention is presumably restricted, regardless of its potential benefits (e.g., because alternative learning programs are deemed more convenient).

Hypothesis 2. *Effort expectancy is necessary for the intention to use personalized learning systems.*

3.3. Social influence

Social influence refers to "the degree to which an individual perceives that important others believe he or she should use the new system" ([31], p. 451). Following Chen [11], important others are understood as people who influence one's learning behavior. This construct had no significant effect on behavioral intention in the sufficiency-based study by Schlagheck & Schewe [14].

Al-Swidi & Faaeg [52] state that social influence might be necessary, although not sufficient, which underlines the need to supplement sufficiency perspectives with a necessity perspective. If important others (such as coworkers and supervisors) do not support or expect the use at all, then employees may feel discouraged from using a learning system (e.g., because they think the important others will not appreciate it and expect to use the working time for other tasks). Thus, without at least some encouragement and influence from others, the formation of behavioral intention may be limited.

Hypothesis 3. *Social influence is necessary for the intention to use personalized learning systems.*

3.4. Facilitating conditions

Facilitating conditions describe "the degree to which an individual believes that an organizational and technical infrastructure exists to support use of the system" ([31], p. 453). While facilitating conditions are sometimes not sufficient (as in the study by Schlagheck & Schewe [14]), their absence may constrain technology adoption.

Notably, this construct encompasses aspects that serve "to remove barriers to use" ([31], p. 453). Therefore, it is reasonable to assume that a certain level of facilitating conditions is needed to achieve behavioral intention. In their absence (e.g., lack of resources and knowledge necessary for usage; [11]), employees may not even consider using a personalized learning system due to a lack of infrastructure. Without a certain extent of facilitating conditions, usage is practically infeasible. NCA findings in the field of AI-generated content support this assumption [42].

Hypothesis 4. *Facilitating conditions are necessary for the intention to use personalized learning systems.*

3.5. Hedonic motivation

Hedonic motivation reflects "the fun or pleasure derived from using a technology" ([10], p. 161). This UTAUT2 construct sheds light on intrinsic motivation and represents "the most important theoretical addition" ([30], p. 223). According to the sufficiency-based findings by Schlagheck & Schewe [14], a learning experience perceived as pleasant fosters employees' intention to use personalized learning systems. However, it is yet to be discovered whether pleasure is merely 'nice-to-have' or even a 'must-have' factor.

The literature on learning technology acceptance contains conclusions about the necessity (e.g., "must ensure and improve trainees' enjoyment […] in order for them to successfully accept and use the training program," [53], p. 886). Back then, there was a lack of appropriate analytical procedures to test necessity [21]. In the meantime, with regard to technologies outside learning contexts, hedonic motivation has indeed been identified as a necessary condition for behavioral intention [36,42,49,54]. Transferred to personalized learning systems, it is reasonable to assume that a lack of hedonic motivation hinders behavioral intention (e.g., when employees perceive other learning activities as more enjoyable or prefer to use their working time for other activities).

Hypothesis 5. *Hedonic motivation is necessary for the intention to use personalized learning systems.*

3.6. Technology trustworthiness

Given that personalized learning systems process sensitive data, it appears crucial to consider their trustworthiness [55], also referred to as trusting beliefs when it comes to technologies [56]. Schlagheck & Schewe [14] investigated the technology itself as a trustee, not the provider. They found no direct effect on behavioral intention but a full mediation through performance expectancy. It should be noted that NCAs always investigate bivariate relationships because a necessary condition "cannot be compensated by other determinants of the outcome" ([21], p. 10). Hence, the two direct paths (H6 and H7) are treated separately, not simultaneously [57].

Using a personalized learning system constitutes a risk-taking behavior [56], and trustworthiness is an antecedent of such behavior [58]. A lack of trust is even designated as a barrier to technology adoption [8]. Specifically, former research identified trust as necessary for usage intention in the field of the mobile sharing economy [45] and medical wearable devices [51]. Against this background, employees are unlikely to form an intention to use a personalized learning system when they hold negative perceptions of its functionality, helpfulness, and reliability [14,59]. Despite other aspects, such as facilitating conditions and hedonic motivation, employees presumably prefer other learning systems if there is a lack of trustworthiness. Accordingly, they would refrain from utilizing a personalized learning system.

Hypothesis 6. *Technology trustworthiness is necessary for the intention to use personalized learning systems.*

In line with previous studies analyzing applications that process sensitive data and knowledge management systems, Schlagheck & Schewe [14] regarded trustworthiness as an antecedent of performance expectancy. If a personalized learning system neither "has the ability to fulfill its tasks [nor] will keep its promises" ([60], p. 1524), it is hard to imagine that it is perceived as useful for learning. That said, this construct presumably acts as a bottleneck for performance expectancy.

Hypothesis 7. *Technology trustworthiness is necessary for performance expectancy.*

4. Method

4.1. Sample and procedures

In order to better contrast the NCA results with findings based on probabilistic sufficiency logic, a previously analyzed dataset was used. Besides, this procedure avoids repeated cost- and time-consuming data collection (e.g., with regard to the time invested by survey participants). With permission, Schlagheck & Schewe's [14] final sample was reused to supplement their sufficiency-based analyses with NCAs. Their data collection took place in the summer of 2020, targeting various industries and occupations. Participation was voluntary and required informed consent. Schlagheck & Schewe [14] already cleaned the raw data based on criteria such as a failed attention check, lack of variance, and suspicious response patterns. In the present study, their final sample of 331 German employees is used to investigate the relationships through a necessity lens.

Personalized learning systems counteract 'one size fits all' approaches by providing flexibility in terms of 'what' and 'how' [25]. These aspects were explicitly stated in the scenario at the beginning of the questionnaire, which served to ensure a shared understanding. It was also emphasized that personalized learning systems offer computer-based, tailor-made learning content, taking into account a learner's individual needs [14].

For their multi-group analyses, Schlagheck & Schewe [14] split the sample into two subgroups per moderator, and Section 5.4 draws upon these subgroups. With regard to gender, the sample comprises 155 male and 176 female participants. Being aware of information losses, Schlagheck & Schewe [14] followed previous studies by also using a dichotomy for age and experience (e.g., [61,62]). The group allocation in terms of age is based on the median, with 169 participants younger than 27 years and 162 participants in the older group. This cutoff demonstrates that young people were overrepresented in the sample, with ages ranging from 19 to 66 years. 191 had little or no experience with personalized learning systems, while 140 were rather experienced.

4.2. Measures

The latent variables were measured on agreement Likert scales ranging from 1 = 'not at all' to 7 = 'fully agree.' Validated scales were adapted for operationalization. The wording by Chen [11] served as a foundation for performance expectancy, effort expectancy, social influence, and facilitating conditions. Besides, formulations by Cheng et al. [61] and Dečman [63] were used for performance expectancy. Items used by Venkatesh et al. [10] were adapted for hedonic motivation, those used by Zhou [60] for technology trustworthiness, and those used by Chao [64] for behavioral intention.

Sample items are: *"I find PLS useful for learning"* (performance expectancy), *"I would find PLS easy to use"* (effort expectancy), *"People who influence my learning behavior think that I should use PLS"* (social influence), *"I would have the knowledge necessary to use PLS"* (facilitating conditions), *"Using PLS is enjoyable"* (hedonic motivation), *"PLS keep their promises"* (technology trustworthiness), *"Assuming I have access to PLS, I intend to use it"* (behavioral intention).

4.3. Preparatory analyses

The analyses were performed in R (version 4.3.1; [65]), particularly with the R package 'NCA' (version 4.0.2; [23]). As mentioned in Section 4.1, existing data used by Schlagheck & Schewe [14] is reused with permission. They have already extensively checked data quality. Moreover, they applied both the common method factor technique and the correlation marker technique, indicating that common method variance is not an issue. Reliability and validity are tested again for the sake of the present study. Table 1 contains Cronbach's alpha, composite reliability, and the average variance extracted for each latent variable under consideration. Cronbach's alpha and the composite reliability always exceeded 0.70. Although the average variance extracted for facilitating conditions was slightly below 0.50 (see Table 1), the construct is retained due to its content-related importance and other satisfied criteria. The Fornell-Larcker criterion is always fulfilled [66]. Computed with the R package 'lavaan' (version 0.6–16; [67]), the measurement model reached an acceptable fit ($\chi^2 = 420.764$, df = 231,

Table 1
Descriptive statistics.

	Min	Max	Mean	SD	CA	CR	AVE	PE	EE	SI	FC	HM	TT	BI
PE	2.00	7.00	5.49	1.03	.91	.91	.68	*.82*						
EE	2.00	7.00	5.62	0.92	.89	.89	.67	.44	*.82*					
SI	1.00	7.00	3.97	1.32	.77	.80	.57	.30	.26	*.75*				
FC	2.00	7.00	5.53	1.02	.72	.71	.46	.43	.59	.33	*.68*			
HM	1.00	7.00	4.73	1.15	.90	.90	.75	.59	.41	.25	.36	*.87*		
TT	2.00	7.00	4.97	0.90	.75	.76	.52	.59	.38	.21	.33	.49	*.72*	
BI	1.67	7.00	5.38	1.13	.86	.87	.68	.63	.45	.39	.46	.54	.47	*.82*

Note. $n = 331$; SD = standard deviation; CA = Cronbach's α; CR = composite reliability; AVE = average variance extracted; PE = performance expectancy; EE = effort expectancy; SI = social influence; FC = facilitating conditions; HM = hedonic motivation; TT = technology trustworthiness; BI = behavioral intention; $p < 0.001$ holds for all bivariate correlations; Italic values on the diagonal correspond to the square root of the average variance extracted.

RMSEA = 0.050 [0.042; 0.057], SRMR = 0.059, CFI = 0.961, and TLI = 0.953). Preparatory for the NCAs, new variables were calculated using the mean of the associated items [19]. An NCA power analysis was run in advance, demonstrating a power of 0.87 for $n = 331$, effect size $d = 0.10$, and $p = 0.05$ [68].

5. Results

5.1. Descriptive statistics

Table 1 includes descriptive statistics. For each construct, the observed maximum equals the theoretical maximum (based on 7-point Likert scales). The observed minimum values range from 1.00 to 2.00, resulting in differing scopes for the bivariate NCAs because empirical values serve as boundaries for the corresponding scope [19]. Setting the scope to $S = (7 – 1)^2 = 36$ based on the theoretical range would have led to larger effects; thus, the chosen default scope is more conservative (see Section 5.3; [69]).

5.2. Hypothesis testing

The hypotheses pertain to necessity ('X is necessary for Y'). Consequently, they are tested using the NCA method, and the guidelines for good NCA practice are applied [19,22]. Scatterplots are shown in Appendix A. They include “ceiling lines that separate the area with observations from the area without observations” ([21], p. 16) and result from ceiling regressions with free disposal hull (CR-FDH). With the CR-FDH ceiling technique, some cases may be above the ceiling line, which is why the accuracy is reported in Table 2. The accuracy is always satisfactory, as <1 % of observations are above the ceiling lines, which is clearly below the threshold of 5 % [21].

Three criteria are used to assess necessity in kind: theoretical justification (here based on UTAUT2 by Venkatesh et al. [10]), practical relevance (based on an effect size of at least 0.10 as proposed by Dul [21]), and statistical significance (based on the permutation test following Dul et al. [70]). Effect sizes correspond to the ratio of the ceiling zone (i.e., the upper-left corner) to the scope. With medium effects ($0.10 \leq d < 0.30$ as suggested by Dul [21]) and $p < 0.001$, the results support H1, H2, and H7 (see Table 2). The first two hypotheses pertain to constructs already contained in the well-known TAM, namely 'perceived usefulness' (equivalent to performance expectancy) and 'perceived ease of use' (equivalent to effort expectancy; [31]). H7 underscores the role of technology trustworthiness as a prerequisite for performance expectancy. Although the NCA for H6 revealed a statistically significant effect, this hypothesis is rejected due to limited practical relevance ($d < 0.10$, corresponding to a small effect; [21]).

The bottlenecks in Table 3 illustrate the 'necessity in degree' [22,71]. Actual values were preferred over percentages, as these appear more tangible [22]. Thus, the anchors 1 and 7 correspond to the 7-point Likert scales. For instance, 4.19 points for performance expectancy are necessary to achieve 7.00 points for behavioral intention. The fact that the entire column for social influence contains 'not necessary' (NN) reflects that its necessity effect size equals zero (see Table 2). Regardless of this construct, between 3.00 and 4.40 points (depending on the condition) are needed in order to reach the maximum level (= 7.00) of behavioral intention or performance expectancy, respectively. The conditions differ with regard to the outcome level at which they become necessary and the slope of the corresponding ceiling line.

Table 2
Necessary condition analyses results.

		Effect size d	*p*-value	Accuracy	Necessity in kind
H1	PE → BI	0.12	< 0.001	99.4 %	yes
H2	EE → BI	0.17	< 0.001	99.1 %	yes
H3	SI → BI	0.00	1.000	100.0 %	no
H4	FC → BI	0.05	0.182	99.7 %	no
H5	HM → BI	0.03	0.358	100.0 %	no
H6	TT → BI	0.09	< 0.001	99.4 %	no ($d < 0.10$)
H7	TT → PE	0.13	< 0.001	99.4 %	yes

Note. $n = 331$; PE = performance expectancy; EE = effort expectancy; SI = social influence; FC = facilitating conditions; HM = hedonic motivation; TT = technology trustworthiness; BI = behavioral intention; NN = not necessary; Effect sizes are based on ceiling regressions with free disposal hull (CR-FDH); 10,000 resamples were used following the NCA guidelines by Dul et al. [22]; Accuracy refers to the ceiling line.

Table 3
Bottleneck levels with actual values.

	PE → BI	EE → BI	SI → BI	FC → BI	HM → BI	TT → BI	TT → PE
1.00	NN	NN	NN	NN	NN	NN	NN
1.50	NN	NN	NN	NN	NN	NN	NN
2.00	NN	NN	NN	NN	NN	NN	NN
2.50	NN	NN	NN	NN	NN	NN	NN
3.00	NN	NN	NN	NN	NN	NN	NN
3.50	NN	2.19	NN	NN	NN	NN	NN
4.00	NN	2.51	NN	NN	NN	2.20	2.26
4.50	2.35	2.82	NN	NN	NN	2.40	2.54
5.00	2.72	3.14	NN	NN	NN	2.60	2.82
5.50	3.08	3.45	NN	2.20	NN	2.80	3.10
6.00	3.45	3.77	NN	2.67	NN	3.00	3.38
6.50	3.82	4.08	NN	3.13	2.00	3.20	3.66
7.00	4.19	4.40	NN	3.60	3.00	3.40	3.94

Note. $n = 331$; PE = performance expectancy; EE = effort expectancy; SI = social influence; FC = facilitating conditions; HM = hedonic motivation; TT = technology trustworthiness; BI = behavioral intention; NN = not necessary; The actual values were measured on a Likert scale ranging from 1 ('not at all') to 7 ('fully agree').

5.3. Robustness checks

Robustness checks were performed to assess “whether the researcher’s conclusion about the necessity hypothesis remains the same (robust result) or differs (fragile result)” ([19], chapter 4.4.1). The results are summarized in Appendix B.

First, the effect size depends on the ceiling line [19]. Given that each variable comprises three to five items rated on 7-point Likert scales, rendering them virtually continuous, the CR-FDH ceiling technique was deemed suitable [21]. The alternative default ceiling line, namely ceiling envelopment with free disposal hull (CE-FDH), would be suitable for “a small number of discrete levels with a jumpy border” ([19], chapter 4.4.1). Robustness checks were run with CE-FDH, resulting in higher effect sizes than before. Consequently, when using CE-FDH, H6 would have been accepted because the threshold considering practical relevance ($d = 0.10$) would be exceeded.

Second, thresholds for assessing necessity in kind should be given consideration. Changing the threshold for the *p*-value from $p < 0.05$ to a stricter value of $p < 0.01$ did not affect the hypotheses assessment. Another decision was the threshold level for the effect size, whereby the established value of $d = 0.10$ was used. Decreasing this value by 0.01 would result in H6 being supported. However, practical relevance decreases with decreasing effect size. Thus, the threshold of $d = 0.10$ was kept.

Third, with regard to the scope, the empirical scope was chosen, as observations are only available for this area. Consequently, the minimum and maximum observed values served as boundaries, corresponding to the default setting in the R package. Technically, it is also possible to use the theoretical scope (i.e., with values ranging from 1 to 7 based on the Likert scales), which would increase the scope and usually lead to larger effects [19]. Indeed, broadening the scope by using the theoretical scope with $S = (7 – 1)^2 = 36$ resulted in larger effects, indicating that the chosen procedure was rather conservative [69].

Fourth, outliers might be an issue. To check whether the results are affected by outliers, the most influential single outlier for each bivariate NCA was inspected [19]. The conclusions remain almost the same, but H6 would have been accepted since the threshold of $d = 0.10$ is reached if the most influential outlier is excluded. In addition, potential multiple outliers were investigated. Deleting one out of three outlier duos would have led to accepting H4. The same applies to one outlier duo for H5 and several outlier duos for H6. However, removing these outliers would be critical as they are neither measurement errors nor sampling errors [57]. In light of the thorough quality checks during data preparation, it is considered reasonable to retain these actual observations as part of the phenomenon [19]. Lastly, following Schlagheck & Schewe [14], two items were excluded due to low factor loadings (si_2 and fc_4). Including these two items in the calculation would not have had any noteworthy effects.

5.4. Subgroup analyses

As highlighted by Troiville et al. [69], “heterogeneity may mask not only sufficiency conditions, but necessity conditions as well” (p. 6). Thus, additional NCAs for subgroups are advisable. Troiville et al. [69] graphically illustrate the importance of conducting NCAs for subsamples. They demonstrate scenarios in which the total sample revealed no necessary condition, but one or both subsamples did, or the total sample revealed a necessary condition, but none or only one of the subsamples did. Consequently, limiting analyses to the total sample could be misleading.

Based on UTAUT2 by Venkatesh et al. [10], and after assessing measurement invariance, Schlagheck & Schewe [14] analyzed potential moderating effects of gender, age, and experience by means of multi-group analyses. The present study follows their group allocation and runs multiple NCAs per subgroup to gain more differentiated insights. Thereby, it is easier to determine whether the necessity of the conditions differs between these groups. Should this be the case, the results would assist practitioners in deriving more targeted interventions. To ensure comparability, the scope was standardized for all subgroups based on the empirical scope of all 331 observations [19].

Appendix C includes the effect sizes, p-values, and assessments of necessity in kind per subgroup. For each subgroup, performance expectancy (H1) was a necessary condition, but the effect sizes differ. The effect was larger for women, the younger group, and participants with little to no experience with personalized learning systems (with d ranging from 0.21 to 0.24) compared to men, older participants, and those with more experience (with d ranging from 0.14 to 0.16). In contrast, effort expectancy (H2) was more necessary for men. Its effect size was at least 0.17 for each subgroup but not statistically significant for the younger and the experienced participants. It turned out that social influence (H3) is not necessary for any subgroup, meaning that its absence is no hindrance to usage intention. The necessity effect of facilitating conditions (H4) was considerably larger for men than for women. Besides, its effect was larger for the older group and equal to zero for the experienced participants. Notably, hedonic motivation (H5) was solely necessary for men and older participants. Except for women, technology trustworthiness was always necessary for behavioral intention (H6) and performance expectancy (H7). The corresponding bottleneck tables are shown in Appendix D.

6. Discussion

6.1. Main findings

The present study supplements previous sufficiency-based findings and highlights the benefit of taking necessity logic into account. After all, the NCA results indicate effort expectancy (H2) to be necessary, which may have been neglected in conclusions restricted to a sufficiency perspective. That would have been a pitfall because a certain level of effort expectancy “must be in place, as there is no additive causality that can compensate for the absence of the necessary cause” ([21], p. 11). This finding of 'necessary but not sufficient' is in line with technology adoption studies in contexts other than learning [18,47].

Moreover, performance expectancy (H1) emerged as a necessary condition for the intention to use personalized learning systems, suggesting that the perceived usefulness for learning is not merely helpful [14] but indispensable. In other words, a certain level is needed for behavioral intention to emerge (see Table 3). In contrast, social influence (H3) was neither necessary nor sufficient, challenging its role in the context of personalized learning systems.

Similarly, the data revealed no necessity in kind for facilitating conditions (H4), which is surprising as they encompass the infrastructure (e.g., necessary resources). Retaining the corresponding null hypothesis may be explained by employees' belief that the facilitating conditions can still be established when needed. However, the corresponding items were formulated using conditional phrasing to reflect the future-oriented scenario, limiting such reasoning. Anyway, the bottleneck table indicates that a value of 3.60 is required for a maximum intention of 7.00 (see Table 3), and this small effect should not be overlooked.

Sufficiency-based results demonstrate that hedonic motivation fosters usage intention [14], whereas the present study revealed no necessity in kind for this potential condition (H5), indicating that pleasure is just 'nice-to-have.' Employees may not consider pleasure essential because a personalized learning system is used in the work context, and the benefits are paramount for them, with no need for pleasure. It is conceivable that applications used in leisure time yield different results (e.g., social media as a pastime, where hedonic motivation may be necessary, but performance expectancy perhaps not; see Shao [36]; or perceived enjoyment in the context of smart shopping carts; see [54]). Nonetheless, as a 'nice-to-have' factor, hedonic motivation is not harmful [14] as long as the effort required for implementing enjoyable features is disregarded. Notably, although there was no 'necessity in kind,' it became necessary for very high levels of intention (see Table 3, which demonstrates 'necessity in degree').

H6, referring to technology trustworthiness as a necessary condition for behavioral intention, was rejected due to the small effect size. Though the statistically significant effect ($d = 0.09$) was slightly below the threshold of 0.10, the latter is only a benchmark rather than a strict rule [21]. Besides potentially decreasing the threshold [19], changing the ceiling technique to CE-FDH, using the theoretical scope, or removing the most influential outlier would have led to accepting this hypothesis (see Section 5.2 and Appendix B). Apart from that, technology trustworthiness was found to be necessary for performance expectancy (H7). Taken together, performance expectancy turned out to be a necessity mediator [57] since H1 and H7 are supported. Accordingly, technology trustworthiness is also viewed as necessary for behavioral intention [57].

Supplementing initial findings on differences between subgroups regarding the necessity of UTAUT constructs [72], some noteworthy differences were found in terms of gender, age, and experience. These findings underline the benefit of separate NCAs per subgroup because some necessity assessments deviate from the results referring to the total sample [69]. Finally, considering differences between subgroups enhances the derivation of specific actions to increase usage intention. For instance, experience might reduce the need for facilitating conditions [73]. When comparing subgroups, one should keep in mind areas without observations within a subgroup (e.g., on the left of the scatterplot). The scope was standardized to the empirical scope of the total sample, which is larger than the empirical scope of some subgroups. Increasing the scope might lead to larger effect sizes, potentially explaining different effect sizes (e.g., when comparing the effect size of 'facilitating conditions' between men and women with $\Delta = 0.12$). Furthermore, the subgroups might have been too small to detect some necessity effects [68].

6.2. Theoretical contributions

This study contributes to the theoretical understanding of technology acceptance in personalized learning by using the emerging NCA method, thereby complementing existing sufficiency-based findings and revealing what is indispensable. Disregarding this causal perspective is a shortcoming of previous studies investigating personalized learning systems. Following necessity logic, if a bottleneck is not fulfilled, it cannot be compensated for by other factors [21]. Consequently, the findings underline the importance of both performance expectancy and effort expectancy. In addition, technology trustworthiness was identified as necessary, calling for inclusion in any model that tries to explain intentions to use personalized learning systems [17]. The NCA findings may also inspire studies involving other learning technologies as they accentuate the benefit of accounting for different causal perspectives (see, for example, the study by Yan & Li [74], who investigated smart education ecology with digital learning power).

Notably, effort expectancy (H2) was identified as necessary, stressing the risk of hasty conclusions if these were solely based on sufficiency logic [20]. After all, although the perceived ease of use was established as a relevant factor in the technology acceptance literature, the sufficiency-based analysis by Schlagheck & Schewe [14] did not reveal a statistically significant effect on usage intention in the context of personalized learning systems. The very small and non-significant necessity effect of hedonic motivation (H5) illustrates that what 'helps' is not always what 'enables' an outcome. Together, these findings underscore the value of combining sufficiency and necessity perspectives to build a more nuanced understanding. Future models of technology adoption may benefit from explicitly distinguishing between 'producers' (sufficiency lens) and 'enablers' (necessity lens) [16,75]. The interest in understanding AI adoption in education is rapidly growing [76], and the bottlenecks identified here might explain why some implementation attempts fail.

Reviewing the literature revealed noticeably more studies conducting NCAs for performance expectancy or effort expectancy than for the remaining UTAUT2 constructs. The present study addresses this shortcoming by additionally accounting for social influence, facilitating conditions, and hedonic motivation. Moreover, technology trustworthiness turned out to be an important extension to the model as it was found to be necessary for performance expectancy. In light of model parsimony [77], social influence may be a candidate for removal when modeling the intention to use personalized learning systems. That said, we are still in the early stages of research, and more empirical evidence is needed to support these findings.

Notwithstanding integrating the NCA method into the field of personalized learning systems, this study went one step further by additionally running NCAs for six subgroups, fostering the scientific discourse in terms of methodology and content. So far, NCA studies seldom distinguish between subgroups [69]. Exemplary exceptions are Cassia & Magno [78], who differentiate users and non-users of anti-waste food applications; Czernietzki et al. [79], who differentiate between AI-based automated and augmented job interviews; and Troiville et al. [69], who differentiate between dairy products and personal care products. As described in Section 5.4, supplementing NCAs for the total sample with NCAs per subgroup helps to avoid misleading conclusions. Therefore, following the call by Troiville et al. [69], NCAs for the total sample were supplemented by NCAs per subgroup. Indeed, the findings indicate differences between subgroups in terms of gender, age, and experience. A statistical test of whether the effect size differs significantly between groups would be helpful, constituting a call for methodological advancements with regard to the emerging NCA method [69].

Notably, Xie et al.'s [80] systematic review of technology-enhanced adaptive/personalized learning did not include any study with working adults as learners. The present study addresses this gap by investigating a neglected research subject in this field. Thereby, the dataset better captures the characteristics of employees. This is important, as they differ from students (e.g., greater heterogeneity and stronger orientation towards practical application; [14]).

6.3. Practical implications

This study shed light on necessity logic, demonstrating the risk of hasty conclusions if practitioners rely solely on findings from a sufficiency perspective. The NCA results offer practice-oriented guidance. This involves assessments of necessity in kind as well as detailed information about bottlenecks that demonstrate necessity in degree [22]. Hereby, the findings highlight the crucial role of performance expectancy, effort expectancy, and technology trustworthiness for the adoption of personalized learning systems. A certain level of a condition is needed to achieve a certain level of a desired outcome, which is depicted in the bottleneck tables [71]. These provide tangible guidance and explain why some implementation processes fail, although UTAUT2 predictors such as social influence and facilitating conditions may have reached high levels. After all, if a bottleneck such as a certain level of performance expectancy or effort expectancy is not fulfilled, this prevents the outcome from occurring [22].

Technological advancements could foster performance expectancy through GenAI-supported features such as chatbots, adaptive content, and automated real-time feedback [4,8,9]. These might raise (unrealistic) expectations regarding an increase in learning performance [12]. If such expectations are not met, the perceived benefit of using a GenAI-enhanced learning system may collapse—undermining its adoption because performance expectancy is a necessary condition. Trustworthiness is likewise essential, as a lack thereof constrains performance expectancy. Thus, when implementing personalized learning systems, particular attention should be paid to signaling technology trustworthiness and communicating it appropriately. An exemplary approach could be video messages from employees serving as testimonials.

Moreover, developers and communication managers must consider effort expectancy as a prerequisite. Given the rapid technological advances, employees might expect seamless, intuitive interactions (e.g., simplified handling based on natural language). If such ease of use is not perceived, the added effort (e.g., for learning how to learn with an AI-enhanced learning system) could hinder usage. Managers should keep in mind inefficiency [19]. After all, the perceived ease of use was found to be necessary but not sufficient [14]. As soon as the bottleneck is reached, further endeavors that increase effort expectancy apparently have no effect on the intention to use. In other words, the usage intention is no longer constrained by this condition [19]. Nevertheless, bearing in mind the greater amount of working time required as well as the potential frustration caused by a difficult operation, it may still be advisable to aim for higher ease of use (but balanced against the associated development costs).

Albeit social influence was neither necessary nor sufficient for the intention to use a personalized learning system, this could be different nowadays and in the future. In light of strategic and ethical questions raised by GenAI [29], endorsement by others might become a legitimizing factor. Besides, this study drew on a hypothetical scenario. In settings where a company has invested money in developing and implementing a specific learning system, the beliefs of important others might indeed affect employees' intention to use the system. Thus, the results of the present study should be regarded as indicative only.

By providing individual support, GenAI potentially enhances facilitating conditions. For the total sample, the dataset revealed neither a relevant necessity effect nor sufficiency [14]. However, based on this single dataset, it cannot be concluded that facilitating conditions are negligible. Moreover, subgroup analyses revealed some effects of medium necessity for this condition. Besides, the construct is an integral part of the UTAUT2 model, which highlights its importance [10].

GenAI-enhanced learning might also yield higher pleasure due to tailored content and, thus, less perceived waste of time. Although hedonic motivation is not necessary for some subgroups, it is a 'nice-to-have' factor, which probably increases the behavioral intention as long as all bottlenecks are fulfilled [14,21]. Moreover, for men and older participants, it was even identified as necessary, highlighting the benefit of subgroup analyses.

Practitioners responsible for implementing learning systems are advised to monitor employees' perceptions with regard to UTAUT2 constructs and trustworthiness. Drawing on this study, they can carry out their own surveys to better account for the organizational context and the characteristics of the specific personalized learning system. Thereby, they can detect which bottlenecks are not yet resolved (e.g., within certain departments or teams) and derive targeted actions. Since the present study revealed different necessity effects in terms of gender, age, and experience, group-specific interventions are recommended. Such subgroup analyses help to adhere to the budget by prioritizing interventions [69]. For instance, as learners become more familiar with personalized learning systems, their assessment of necessary conditions may change. Focus group interviews could provide insights that supplement these quantitative analyses. Using NCA provides a complementary but not exhaustive perspective on behavioral intention. While this study identified conditions that are necessary, it does not account for factors that may be sufficient or jointly interactive in complex ways [15]. As such, the findings should be interpreted alongside other analytical approaches, including results from qualitative studies, which are rather seldom in the field of AI-supported learning [81].

6.4. Limitations and future research directions

Despite offering novel insights into necessary conditions for the intention to use personalized learning systems, this study has some limitations that offer starting points for future research. First, effect sizes may vary over time, along with shifting ceiling intercepts and slopes [19]. The present study used an existing dataset, ensuring comparability with the sufficiency-based findings of Schlagheck & Schewe [14]. However, their data collection took place in 2020, and recent technological advancements could yield different necessity effect sizes. Although personalization through computer-assisted tailoring was emphasized in the questionnaire, GenAI was not yet a thing back then, which is why GenAI was not explicitly mentioned. Against this background, future studies could adopt the GenAI Acceptance Scale by Yilmaz et al. [26].

Second, the study focused on conditions derived from the widely recognized UTAUT2 model. While this provides a solid theoretical foundation, other necessary conditions may exist beyond those included. For instance, in light of the General Data Protection Regulation and the privacy awareness among German employees, it is conceivable that local data storage is viewed as a prerequisite. Similarly, the recognition of learning time as paid working time could constitute another necessary condition. In the questionnaire, both aspects were stated as given in the scenario presented to survey participants. Future studies may address the necessity of these and other aspects, such as perceived credibility [82], individual learning intention [83], as well as the omitted UTAUT2 constructs, namely price value and habit [16,50]. Moreover, users' expectations and changes over time should be accounted for when investigating the adoption of AI-enhanced learning [12].

Third, the items referred to a hypothetical personalized learning system. Thus, the findings are limited to usage intentions. Repeating the study in the context of a real-world learning system would demonstrate whether similar necessity patterns emerge. Besides, examining actual usage alongside usage intentions through a necessity lens would provide a more holistic understanding (see, for example, Frommeyer et al. [84], who investigated sustainable buying behavior). Apart from that, applying the NCA method to other learning systems and contexts is encouraged to explore whether necessity effect sizes and bottlenecks are consistent or domain-specific. Likewise, cultural aspects deserve attention, as Erdmann & Toro-Dupouy [85] found differences between continents regarding the importance of effort expectancy. Finally, with the growing number of studies that conduct NCAs in the field of technology adoption, a meta-analysis would be useful.

7. Conclusion

AI-based adaptive learning tools, such as personalized learning systems, are gaining increasing attention. The present study addressed learners' perceptions of personalized learning systems through a necessity lens. Thereby, it stirs up theoretical discussions on their adoption and provides tangible guidance for practitioners about conditions that must be present to achieve employees' usage intention.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author used ChatGPT in order to obtain feedback on clarity and persuasiveness from the perspective of an editor, a reviewer, and the audience. After using this tool/service, the author reviewed and edited the content as needed and takes full responsibility for the content of the publication.

Glossary

Necessary condition analysis (NCA) = "a method that combines necessity causality (rather than common probabilistic or configurational causality) and a related data analysis technique (ensuring theory-method fit)" ([19], chapter 1.8).

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Transparency statement

The present study uses the same data as Schlagheck & Schewe [14]. Schlagheck is my maiden name. Inspired by Dul et al. [17], I reused the data to investigate the intention to use personalized learning systems from another causal perspective.

CRediT authorship contribution statement

Sandra Limberg: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The author declares that she has no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A

Fig. A1

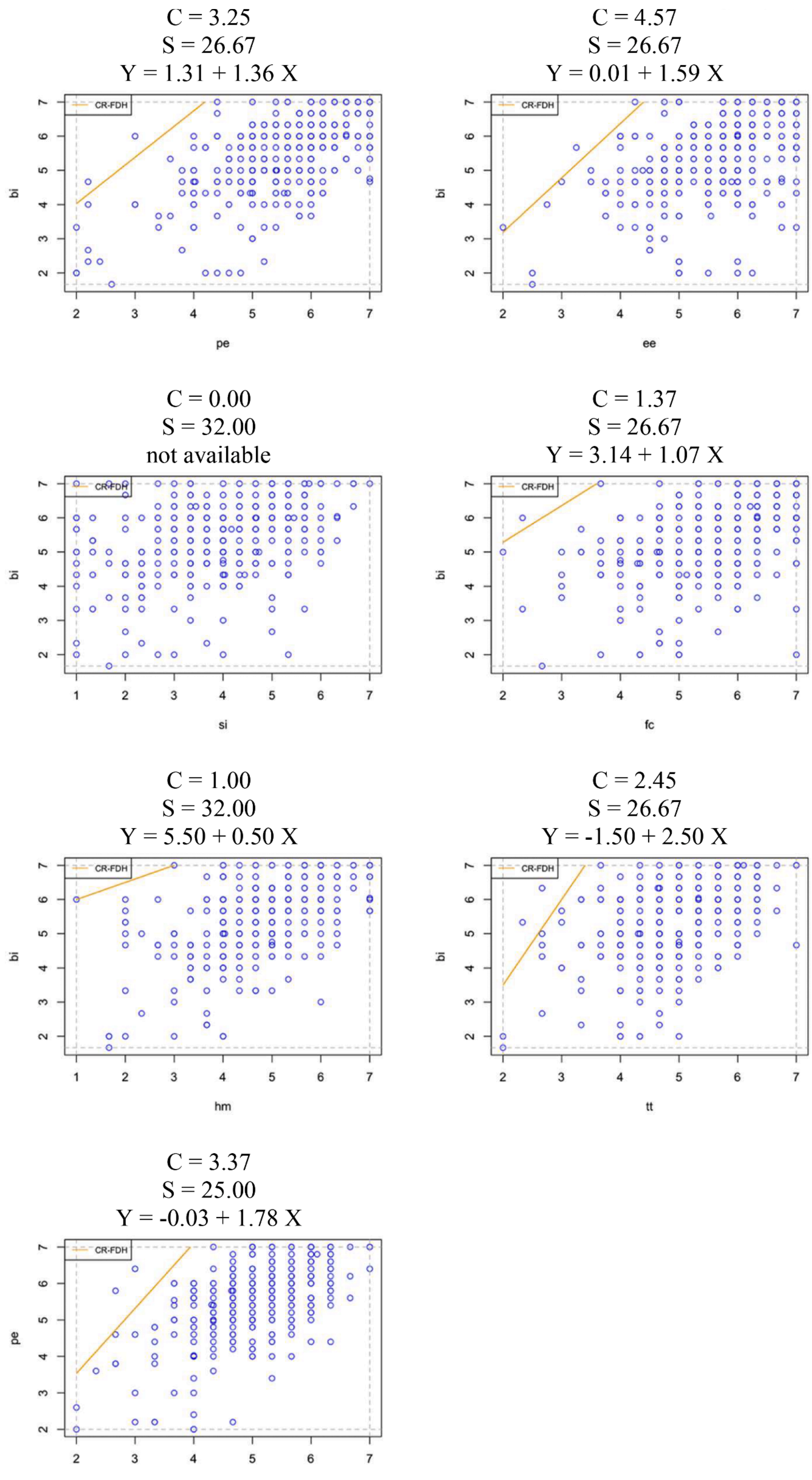

Fig. A1. Scatterplots including ceiling lines.
Note. $n = 331$; PE = performance expectancy; EE = effort expectancy; SI = social influence; FC = facilitating conditions; HM = hedonic motivation; TT = technology trustworthiness; BI = behavioral intention; *C* = ceiling zone; *S* = scope; CR-FDH = ceiling regression with free disposal hull.

Appendix B

Table B1

Table B1
Robustness table.

Robustness check	Effect size	*p*-value	Necessity	Effect size	*p*-value	Necessity
	PE → BI			**EE → BI**		
Original	0.12	< 0.001	yes	0.17	< 0.001	yes
Ceiling change	0.15	< 0.001	yes	0.20	< 0.001	yes
p threshold change	0.12	< 0.001	yes	0.17	< 0.001	yes
Scope change	0.19	< 0.001	yes	0.25	< 0.001	yes
Single outlier removal	0.16	< 0.001	yes	0.14	< 0.001	yes
Multiple outlier removal	0.19	< 0.001	yes	0.14	< 0.001	yes
	SI → BI			**FC → BI**		
Original	0.00	1.000	no	0.05	0.182	no
Ceiling change	0.00	1.000	no	0.08	0.132	no
p threshold change	0.00	1.000	no	0.05	0.182	no
Scope change	0.00	1.000	no	0.10	0.388	no
Single outlier removal	0.00	1.000	no	0.08	0.041	no
Multiple outlier removal	0.00	1.000	no	0.12	0.003	yes
	HM → BI			**TT → BI**		
Original	0.03	0.358	no	0.09	< 0.001	no
Ceiling change	0.06	0.244	no	0.11	0.001	yes
p threshold change	0.03	0.358	no	0.09	< 0.001	no
Scope change	0.03	0.358	no	0.20	0.001	yes
Single outlier removal	0.08	< 0.001	no	0.12	< 0.001	yes
Multiple outlier removal	0.13	< 0.001	yes	0.04	0.159	no
	TT → PE					
Original	0.13	< 0.001	yes			
Ceiling change	0.15	< 0.001	yes			
p threshold change	0.13	< 0.001	yes			
Scope change	0.21	< 0.001	yes			
Single outlier removal	0.17	< 0.001	yes			
Multiple outlier removal	0.19	< 0.001	yes			

Note. $n = 331$; PE = performance expectancy; EE = effort expectancy; SI = social influence; FC = facilitating conditions; HM = hedonic motivation; TT = technology trustworthiness; BI = behavioral intention; The established threshold for the effect size of $d = 0.10$ with $p < 0.05$ was used to assess necessity in kind.

Appendix C

Table C1

Table C1
Necessary condition analyses results (per subgroup).

	Effect size	*p*-value	Necessity	Effect size	*p*-value	Necessity
Gender	**Male ($n = 155$)**			**Female ($n = 176$)**		
PE → BI	0.14	< 0.001	yes	0.23	< 0.001	yes
EE → BI	0.25	0.001	yes	0.19	< 0.001	yes
SI → BI	0.02	0.206	no	0.00	1.000	no
FC → BI	0.23	0.044	yes	0.11	0.003	yes
HM → BI	0.20	< 0.001	yes	0.03	0.627	no
TT → BI	0.12	< 0.001	yes	0.04	0.428	no
TT → PE	0.20	< 0.001	yes	0.09	0.039	no
Age	**Younger ($n = 169$)**			**Older ($n = 162$)**		
PE → BI	0.24	< 0.001	yes	0.15	< 0.001	yes
EE → BI	0.19	0.083	no	0.17	< 0.001	yes
SI → BI	0.00	1.000	no	0.02	0.065	no
FC → BI	0.10	0.055	no	0.16	0.004	yes
HM → BI	0.06	0.228	no	0.18	< 0.001	yes
TT → BI	0.17	< 0.001	yes	0.13	0.001	yes
TT → PE	0.17	< 0.001	yes	0.20	< 0.001	yes
Experience	**Lower ($n = 191$)**			**Higher ($n = 140$)**		
PE → BI	0.21	< 0.001	yes	0.16	< 0.001	yes
EE → BI	0.19	< 0.001	yes	0.35	0.124	no
SI → BI	0.02	0.153	no	0.00	1.000	no
FC → BI	0.10	0.057	no	0.00	1.000	no
HM → BI	0.05	0.493	no	0.09	0.053	no
TT → BI	0.19	< 0.001	yes	0.12	< 0.001	yes
TT → PE	0.18	< 0.001	yes	0.17	< 0.001	yes

Note. PE = performance expectancy; EE = effort expectancy; SI = social influence; FC = facilitating conditions; HM = hedonic motivation; TT = technology trustworthiness; BI = behavioral intention; The respective scope was determined based on the empirical scope of the total sample (see Table 1 for the minimum and maximum observed values per construct); The established threshold for the effect size of $d = 0.10$ with $p < 0.05$ was used to assess necessity in kind.

Appendix D

Tables D1 and D2, D3

Table D1
Bottleneck levels with actual values (per subgroup by gender).

	PE → BI		EE → BI		SI → BI		FC → BI		HM → BI		TT → BI		TT → PE	
	M	F	M	F	M	F	M	F	M	F	M	F	M	F
1.00	NN	NN	-	NN	NN	NN	-	NN	NN	NN	NN	NN	NN	NN
1.50	NN	NN	-	NN	NN	NN	-	NN	NN	NN	NN	NN	NN	NN
2.00	NN	NN	2.27	NN	NN	NN	2.73	NN	NN	NN	NN	NN	NN	NN
2.50	NN	NN	2.47	NN	NN	NN	2.82	NN	NN	NN	NN	NN	NN	NN
3.00	NN	NN	2.68	NN	NN	NN	2.92	NN	1.28	NN	NN	NN	NN	NN
3.50	2.06	2.23	2.89	2.05	NN	NN	3.01	NN	1.60	NN	2.16	NN	NN	NN
4.00	2.36	2.67	3.09	2.44	NN	NN	3.10	NN	1.92	NN	2.37	NN	2.35	NN
4.50	2.65	3.12	3.30	2.84	NN	NN	3.20	NN	2.24	NN	2.57	NN	2.77	NN
5.00	2.95	3.56	3.51	3.24	NN	NN	3.29	NN	2.57	NN	2.78	NN	3.19	NN
5.50	3.24	4.00	3.71	3.64	NN	NN	3.39	2.27	2.89	NN	2.99	NN	3.62	2.43
6.00	3.54	4.44	3.92	4.04	1.22	NN	3.48	3.40	3.21	NN	3.20	NN	4.04	3.16
6.50	3.83	4.88	4.13	4.44	1.47	NN	3.57	4.52	3.53	2.00	3.41	3.08	4.46	3.90
7.00	4.13	5.32	4.33	4.83	1.72	NN	3.67	5.64	3.85	3.00	3.62	4.33	4.88	4.64

Note. $n = 155$ (male) and 176 (female); PE = performance expectancy; EE = effort expectancy; SI = social influence; FC = facilitating conditions; HM = hedonic motivation; TT = technology trustworthiness; BI = behavioral intention; *M* = male; *F* = female; - = step below scope; NN = not necessary; The actual values were measured on a Likert scale ranging from 1 ('not at all') to 7 ('fully agree').

Table D2
Bottleneck levels with actual values (per subgroup by age).

	PE → BI		EE → BI		SI → BI		FC → BI		HM → BI		TT → BI		TT → PE	
	Y	O	Y	O	Y	O	Y	O	Y	O	Y	O	Y	O
1.00	NN	NN	NN	NN	NN	NN	NN	NN	NN	-	NN	NN	NN	NN
1.50	NN	NN	NN	NN	NN	NN	NN	NN	NN	-	NN	NN	NN	NN
2.00	NN	NN	NN	NN	NN	NN	NN	NN	NN	1.37	NN	NN	NN	NN
2.50	2.22	NN	NN	NN	NN	NN	NN	2.13	NN	1.53	NN	NN	NN	NN
3.00	2.48	NN	NN	NN	NN	NN	NN	2.32	NN	1.68	NN	2.04	NN	2.17
3.50	2.74	NN	NN	2.17	NN	NN	NN	2.50	NN	1.83	NN	2.24	NN	2.44
4.00	3.00	NN	2.32	2.50	NN	NN	NN	2.68	NN	1.98	2.36	2.44	2.16	2.71
4.50	3.26	2.33	2.76	2.82	NN	NN	NN	2.87	NN	2.14	2.74	2.64	2.57	2.98
5.00	3.52	2.81	3.20	3.15	NN	NN	NN	3.05	NN	2.29	3.12	2.83	2.98	3.26
5.50	3.78	3.29	3.63	3.48	NN	NN	2.23	3.24	NN	2.44	3.50	3.03	3.39	3.53
6.00	4.04	3.77	4.07	3.80	NN	NN	3.31	3.42	1.06	2.60	3.88	3.23	3.79	3.80
6.50	4.30	4.24	4.50	4.13	NN	1.50	4.39	3.61	3.01	2.75	4.26	3.43	4.20	4.07
7.00	4.56	4.72	4.94	4.46	NN	2.00	5.47	3.79	4.95	2.90	4.64	3.62	4.61	4.34

Note. $n = 169$ (younger) and 162 (older); PE = performance expectancy; EE = effort expectancy; SI = social influence; FC = facilitating conditions; HM = hedonic motivation; TT = technology trustworthiness; BI = behavioral intention; *Y* = younger; *O* = older; - = step below scope; NN = not necessary; The actual values were measured on a Likert scale ranging from 1 ('not at all') to 7 ('fully agree').

Table D3
Bottleneck levels with actual values (per subgroup by experience).

	PE → BI		EE → BI		SI → BI		FC → BI		HM → BI		TT → BI		TT → PE	
	L	H	L	H	L	H	L	H	L	H	L	H	L	H
1.00	NN	NN	NN	-	NN	NN	NN	NN	NN	NN	NN	NN	NN	NN
1.50	NN	NN	NN	-	NN	NN	NN	NN	NN	NN	NN	NN	NN	NN
2.00	NN	NN	NN	3.31	NN	NN	NN	NN	NN	NN	NN	NN	NN	NN
2.50	NN	NN	NN	3.41	NN	NN	NN	NN	NN	NN	NN	NN	NN	NN
3.00	NN	NN	NN	3.50	NN	NN	NN	NN	NN	NN	NN	NN	NN	2.11
3.50	NN	2.22	2.03	3.59	NN	NN	NN	NN	NN	NN	2.07	2.16	NN	2.35
4.00	NN	2.49	2.44	3.69	NN	NN	NN	NN	NN	NN	2.46	2.37	2.24	2.60
4.50	2.57	2.76	2.85	3.78	NN	NN	NN	NN	NN	1.14	2.86	2.57	2.67	2.84
5.00	3.22	3.04	3.26	3.88	NN	NN	NN	NN	NN	1.55	3.25	2.78	3.09	3.08
5.50	3.87	3.31	3.67	3.97	NN	NN	2.23	NN	NN	1.96	3.65	2.99	3.52	3.32
6.00	4.53	3.59	4.08	4.06	NN	NN	3.31	NN	NN	2.37	4.05	3.20	3.95	3.56
6.50	5.18	3.86	4.49	4.16	1.50	NN	4.39	NN	2.50	2.78	4.44	3.41	4.38	3.81
7.00	5.83	4.13	4.90	4.25	2.00	NN	5.47	NN	4.00	3.20	4.84	3.62	4.81	4.05

Note. $n = 191$ (lower) and 140 (higher); PE = performance expectancy; EE = effort expectancy; SI = social influence; FC = facilitating conditions; HM = hedonic motivation; TT = technology trustworthiness; BI = behavioral intention; *L* = lower; *H* = higher; - = step below scope; NN = not necessary; The actual values were measured on a Likert scale ranging from 1 ('not at all') to 7 ('fully agree').

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