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Responsible Use of Digital Health Technologies: A Configurational Analysis of Traits, Beliefs, and Competencies

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Abstract

Digital health technologies offer benefits but also pose risks such as privacy breaches and algorithmic bias, necessitating their responsible use beyond mere adoption. This study explores which configurations of individual traits, beliefs, and competencies are associated with responsible use of digital health technologies. Using fsQCA on data from 62 participants, we analyze configurations of IT mindfulness, eHealth literacy, trusting beliefs, ethical awareness, and computer self-efficacy of high and low responsible use. The analysis points to two empirically distinct profiles: critically engaged users with higher responsible use, and competent but uncritical users with lower responsible use despite comparable technical competencies. Counterintuitively, lower trusting beliefs are associated with responsible use, whereas higher trusting beliefs are associated with lower responsible use, pointing to a boundary condition of adoption-centered trust logic in post-adoptive normative contexts. The study suggests that some trusting beliefs may dampen the critical evaluation required for responsible use and indicates that technical competence alone does not reliably distinguish higher from lower responsible use. We contribute to emerging digital responsibility research by offering exploratory evidence on how individual-level traits, beliefs, and competencies may relate to responsible use in digital health. Practical implications include developing interventions that cultivate ethical awareness, productive skepticism, and sustained mindfulness rather than merely building trust or teaching technical skills.

CCS Concepts

• **Social and professional topics**;

Keywords

Digital Responsibility; Responsible Use; Post-adoptive Use; Digital Health

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1 Introduction

Digital health technologies can improve care, but the same technologies can also create harm [58]. Among others, they can reduce medical errors and improve access to healthcare, yet they come with the downside of amplifying privacy breaches, surveillance, and algorithmic bias [12, 70, 44]. Given these mixed outcomes, it depends on how individuals use them. This shifts attention beyond commonly studied outcomes such as adoption toward responsible use, which may shape whether digital health technologies generate benefits without amplifying harm.

Initial IS research in those streams explains why users accept and use technologies in multiple contexts [67], which is then complemented by post-adoptive research that further explains how individuals use technologies after adoption [27]. This work advances our understanding of technology use, but it does not directly explain how users evaluate and enact responsible use when the same technology can generate both benefits and harms. This is due to the typical dependent variables (e. g., intention, usage, continued or feature use) that consider *more or better use* as desirable and, thus, rather ignore the normative judgment and stakeholder-oriented accountability that is required to understand responsible use. For example, given that technology use in digital health is accompanied by concerns about security, privacy, or fairness issues [1, 32, 70], the question of why some individuals use a technology despite questioning it is theoretically distinct from explaining why they use it at all.

Research on digital responsibility provides a helpful lens for this distinction. Digital responsibility lets us conceptualize responsibility in digital contexts as comprising accountability for outcomes, an obligation to facilitate benefits while protecting against harms, and dependability as a sustained commitment over time [56]. Translating this to the individual level, this view centers accountability for technology-related consequences for affected stakeholders, a challenge that is increasingly difficult in complex digital environments [13]. Consequently, we need a theoretical and empirical understanding of when and why individuals practice digital responsibility in their use of digital health technologies. In this study, we use the term digital health technologies to refer to consumer-facing and voluntarily used tools that individuals use for self-monitoring, personal health information retrieval, and wellness tracking outside of formal clinical settings (e. g., fitness trackers, symptom checkers, or health apps). While some research has discussed responsibility and responsible use in a conceptual way [e. g., 56, 13, 8], individual- or consumer-level responsible use has received little attention in core health IS research, which has focused predominantly on adoption, institutional implementation, and data-driven decision support [68]. We complement this work by examining, from a configurational perspective, how individual traits, beliefs, and competencies jointly relate to responsible use, particularly when convenience benefits may encourage uncritical reliance. We address this problem by using digital responsibility as a lens to define responsible use of digital health tools and ask: **Which configurations of individual traits, beliefs, and competencies foster responsible use of digital health technologies?**

The focus of this study is on individuals in the role of consumers who voluntarily use digital health technologies for self-monitoring, accessing health information, and tracking their personal well-being, as key actors. We examine IT mindfulness, ethical awareness, trusting beliefs, computer self-efficacy, and eHealth literacy and use fuzzy-set qualitative comparative analysis (fsQCA) to understand how these result in responsible use.

2 Theoretical Background

2.1 Post-adoptive Use of Digital Technologies

Post-adoptive IS research provides a theoretical understanding of how individuals use technologies after adoption [27].

Though traditional adoption research is helpful to understand intentions or adoption behavior and points to focus on antecedents of adoption [4, 67], neither does it directly explain whether the subsequent use is responsible given the potential for both benefits and harms to individuals, nor the dynamic nature of usage behaviors over time. Recent IS research therefore suggests viewing technology usage through the lens of an IS use lifecycle, which differentiates distinct phases from pre-adoption and trial to post-adoption, discontinuance, and potential resumption [31, 30]. Within this lifecycle, post-adoptive use is a critical phase where individuals continuously adapt and explore technology features and integrate them into their routines [27]. This perspective complements the understanding of responsible use as a continuous evaluation process [13] that occurs during the post-adoptive phase of the lifecycle.

Taken together, this literature provides a well-established theoretical and empirical base for studying technology use after adoption. However, it overlooks the normative evaluation required to explain responsible use in settings where use can influence other stakeholders or individuals beyond the focal user. The healthcare domain illustrates this issue well. Digital health technologies are not simply a subset of digital technologies: They carry direct implications for health decisions and individual well-being, operate in an environment constrained by regulatory frameworks such as the EU AI Act or data protection regulations, and involve highly sensitive personal health data [17, 58]. Unlike in general consumer contexts, the stakes in digital health extend to privacy, physical outcomes, and indirectly affected stakeholders [17]. Responsible use in the digital health context therefore requires that users engage not only with the technical features of a system, but also with the ethical and regulatory environment specific to health data, for instance when continuous data collection or opaque data flows to third parties raise risks that users often do not fully anticipate [70].

2.2 Responsible Use of Digital Technologies

Responsible use is characterized by a forward-looking evaluation of consequences that is not anticipated by traditional ethical research in digital contexts. So far, established ethical theories and models argue that user behavior is proximate in space and time and that consequences are foreseeable [24]. Digital technologies extend the reach of user behavior across time and space and so create cumulative, indirect, or difficult-to-reverse consequences for other stakeholders [24, 69, 13]. Consequently, responsibility in digital contexts cannot be reduced to retrospective liability [13, 9].

Recent IS research conceptualizes Digital Responsibility (DR) as a dynamic, multidimensional construct comprising accountability for outcomes, the obligation to protect against negative consequences while facilitating positive consequences, and dependability as a sustained commitment over time [56]. Rather than a fixed state, responsibility in the digital age is a "process of becoming" [13, p. 1296]. At the individual level, this perspective emphasizes answerability, that is, the capacity to provide reasons for the technology use and its consequences for other stakeholders [9]. It requires users to remain epistemically aware of their actions and resist the comfort of blind reliance on technology [9].

Building on this view, we define responsible use of technologies as a pattern of use in which individuals critically reflect on consequences and adjust their use to reduce potential harms and support potential benefits for stakeholders (see Table 4 in Appendix for definitions of related concepts). This definition treats responsible use as a post-adoptive outcome that depends on how individuals evaluate consequences and adjust their use accordingly, rather than on whether they use a technology at all. Consistent with the consumer-oriented digital health context of this study, responsible use is enacted by lay individuals, not clinical professionals, who voluntarily engage with technologies and lack the professional accountability structures characteristic of clinical settings.

2.3 Configurational Perspective and Determinants

Responsible use is likely produced by combinations of individual conditions rather than by single, symmetric net effects. Prior research shows that IS-related behaviors are often asymmetric: different configurations of conditions can be sufficient for the same outcome, and conditions that support an outcome need not mirror conditions associated with its absence [28, 49]. Configurational approaches capture such equifinal, asymmetric relationships by modeling how conditions jointly influence an outcome [18, 28]. This perspective has been frequently applied to individual-level behavior and is particularly helpful when individual differences interact and when specific conditions may be necessary only in combination with others [48, 39].

Accordingly, we examine responsible use through a configurational lens and focus on three domains of individual differences that map onto responsible use requirements: IT-specific traits that shape attentive engagement, beliefs that shape reliance and ethical evaluation, and contextual competencies that shape users' ability to assess and act on domain-relevant information. We operationalize these with five determinants through computer self-efficacy, IT mindfulness, eHealth literacy, trusting beliefs, and ethical awareness.

Computer Self-Efficacy (CSE). We position computer self-efficacy as the perceived capability foundation for using digital health technologies that is relevant for responsible use as a post-adoptive behavior. Specifically, CSE reflects an individual's belief that they can use technology effectively in specific situations [11, 10]. Prior work links CSE to more positive technology evaluations and continued use [66, 10] and shows that CSE interacts with cognitive factors, such as trust, which jointly influence post-adoptive use behaviors [59, 33]. For responsible use, we understand CSE as the perceived capability to use technology features and settings that are needed for critical reflections beyond a driver of simple usage.

IT Mindfulness (ITM). We also argue that IT mindfulness supports responsible use as it promotes attentive or even detail-oriented technology use. Well-established research considers ITM as a mindset in which users focus on the present, attend to detail, consider alternative uses, and show interest in trying technology features [62]. It includes multiple dimensions such as alertness to distinctions and awareness of multiple perspectives [62] that together influence post-adoptive behaviors [16, 26]. Applying this to digital health contexts, ITM has the potential to facilitate responsible use by increasing the likelihood that users recognize the implications of their behaviors, evaluate outputs and adjust their technology use in the presence of concerns.

eHealth Literacy (eHL). We consider eHealth literacy as a factor that supports responsible use because it enables users to search for, interpret, assess, and make use of digital health information in ways that enable informed evaluation. eHL refers to the ability to use digital resources to address health issues through locating, understanding, evaluating digital health information [43], and has been extended to navigating digital technologies effectively, safely, and in ways that foster the achievement of health-related goals [41]. As a domain-specific competency, it integrates digital, health, and information literacy in electronic health contexts [43, 40]. Because responsible use in digital health requires the evaluation of output and information quality, eHL is likely to support the user's ability to critically assess recommendations and implications of technology use [41].

Trusting Beliefs (TB). Trusting beliefs are at the core of explaining post-adoptive use. Notably, we consider their role in responsible use as theoretically ambivalent because they can facilitate use and reduce critical evaluation, which can potentially lead to misuse or overreliance [20]. TB capture the confident perception that the trustee possesses qualities that serve the trustor's interests [38, 25]. TB typically include competence, benevolence, and integrity [38, 7, 36] and relate to post-adoptive and extended use [60, 59]. For responsible use, TB increase the likelihood to rely on digital health technologies, but, notably, strong TB may also reduce the motivations to question outputs and evaluate consequences critically.

Ethical Awareness (EA). Ethical awareness supports responsible use by increasing the chance that users recognize ethically relevant aspects of technology use and consider consequences for other stakeholders. EA reflects the ability to notice, on the one hand, how one's own behavior influences others and, on the other hand, to detect the ethical dimensions of a given situation [3, 64]. In digital health, ethical consequences are often not immediately apparent, which makes it even more important to recognize risks regarding privacy, misinformation, exclusion, and misuse during use. Higher EA should therefore increase the probability that users evaluate implications beyond personal convenience and adjust their use accordingly.

In sum, we consider responsible use (RU) as a post-adoptive behavior that is predisposed by configurations of IT-specific traits (ITM), beliefs (TB, EA), and contextual competencies (CSE, eHL) (Figure 1). Consistent with configurational logic [49], configurations associated with less responsible use might differ from those configurations associated with more responsible use.

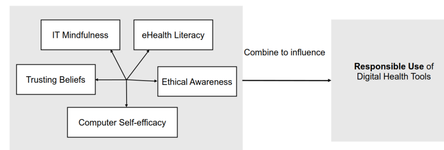

Figure 1: Research Model for Responsible Use of Digital Health Technologies.

3 Research Method

To investigate our research question, we perform a fuzzy-set Qualitative Comparative Analysis (fsQCA) to analyze data gathered from 62 participants. We followed the guidelines by Mattke et al. [35].

3.1 Survey Design and Data Collection

To examine the research model, we prepared an online survey using established and validated scales for the determinants. Participants were recruited through convenience sampling via university channels and participation calls. For responsible use, we adapted items from prior post-adoptive use and responsible use research and followed scale-development guidance [14]. All utilized measurement items for this study, along with their corresponding scales and sources, are listed in Table 1.

To ensure that participants provide accurate responses, we included an attention check [23], which resulted in 62 participants (Table 2). We followed tests for indicator reliability, construct reliability, discriminant validity, and common method bias [35]. One ethical awareness item with low loading was dropped (EA3, loading: 0.663). All items exceeded 0.707 for indicator reliability. CR exceeded 0.70; AVE and CA exceeded 0.50 and 0.70, respectively (Table 3). Discriminant validity was confirmed [22]. The sample size is adequate for QCA (ratio: 0.08) [34]. Common method bias is unlikely according to Harman's test result of 18.98% [50].

3.2 Data Analysis

FsQCA uses set theory and Boolean logic to derive necessary combinations for outcomes [55] and allows equifinality and asymmetry [19]. Concerning equifinality, this approach makes it possible to identify multiple pathways that lead to the same outcome [19]. Therefore, fsQCA enables the study of individual factors within profiles rather than examining them individually. Regarding asymmetry, fsQCA allows individual factor configurations that lead to lower values of responsible use (indicated by ~RU) to not necessarily be the opposite of configurations that lead to higher responsible use [19].

Table 1: Overview of Variables.

Variable	Sample Item (or all items for self-developed)	Loadings (for self-developed)	Source (adapted from)
IT mindfulness	I am very creative when using health technologies.		[62]
Trusting beliefs	The health technology is capable of supporting my health.		[6]
Computer self-efficacy	I could use the health technology if there was no one around to tell me what to do.		[61, 11]
Ethical awareness	I notice that there are ethical issues involved in human interaction.		[64]
eHealth literacy	I know what health resources are available on the internet.		[42]
Responsible use	When using health technologies, I always recognize possible unintended long-term consequences.	.824	Self-developed
	When using health technologies, I always recognize possible indirect implications for others.	.815	
	When using health technologies, I am well aware that my behavior could have consequences for others.	.802	
	When using health technologies, I always reflect on both potentially harmful and beneficial outcomes.	.782	
	I always think of how I can mitigate negative impacts of health technologies when using them.	.791	
	I always consider positive and negative consequences of health technologies.	.778	
	I always critically reflect on my use of health technologies.	.794	

We followed common guidelines and recommendations for the application of fsQCA in the IS discipline, adhering to the seven-step framework suggested by Mattke et al. [35].

First, we converted survey data into fuzzy sets ranging from 0 to 1 [52]. Following IS research [48, 28], we used direct calibration with anchors, using the value 6 for full membership, 2 for full non-membership, and 4 as the cross-over point [35, 39, 45]. We added 0.001 to values of 0.50 to prevent exclusion by the algorithm [35, 19]. Next, we tested for necessary conditions requiring a consistency of 0.90, coverage of 0.60, and Relevance of Necessity of 0.60 [63, 35]. We did not identify any necessary conditions. Hence, no variable was always present for any specific outcome [52].

Next, we calculated truth tables for both outcomes (high vs. low RU), comprising 32 configurations of conditions to confirm an appropriate number of configurations. To reduce the truth table to include only sufficient configurations, we applied a frequency threshold of 2 [19, 54], retaining 93.5% of observations, raw consistency threshold of 0.75 [52, 35], and proportional reduction of inconsistency (PRI) threshold of 0.75 [21, 35]. We applied the Quine-McCluskey algorithm, which resulted in one sufficient configuration for each outcome. As the last step, we identified the parsimonious solutions by utilizing both "easy" and "difficult" counterfactuals as outlined by Park et al. [47]. To distinguish between core and peripheral conditions, we compared the intermediate and parsimonious solutions, following the approach described by Fiss [19]. Core conditions are those that exhibit a strong causal influence on the outcome within a sufficient configuration, whereas peripheral conditions show a weaker causal effect. Finally, we integrated the intermediate and parsimonious solutions to determine which conditions were core and which were peripheral. Sensitivity tests on the sample and data calibration confirmed the robustness of results [46]. Table 5 provides an overview of the validation measures.

4 Results

For responsible use, the analysis for sufficient conditions revealed one configuration. Similarly, for low responsible use, the analysis identified one sufficient configuration. The revealed configurations were evaluated regarding their quality based on consistency, raw coverage, and unique coverage. The consistency scores of 0.90 of both sufficient configurations surpass the minimal required threshold of 0.75, indicating good consistency [53, 57]. The empirical relevance for each sufficient configuration can be estimated by considering their raw and unique coverage. Raw coverage ranges from 0.40 for RU to 0.42 for ~RU. RU has a unique coverage of 0.40, whereas the value for the configuration for ~RU is 0.42. These moderate coverage values indicate that the identified configurations are sufficient but not exhaustive, as a relevant share of outcome membership remains unexplained. This suggests that the same outcomes can be produced by additional configurations not captured in this study, i. e., responsible use is likely to be equifinal [19]. As the analysis identified one sufficient configuration for each outcome, solution coverage and solution consistency scores are identical to the corresponding individual scores described above. For both configurations, all these values meet the minimum required specifications [35]. Figure 2 presents the revealed sufficient configurations. In line with current practices in configurational IS research [39,

Table 2: Characteristics of 62 Survey Participants.

Demographics	%	
Age		
18 and younger	0.00	
19–24	41.94	
25–30	45.16	
31–36	6.45	
37–44	3.23	
45 and older	3.23	
Gender		
Male	62.90	
Female	37.10	
Other	0.00	
Education		
High school	24.19	
Lower degree	0.00	
Bachelor’s degree	48.38	
Master’s degree	22.58	
Doctorate	4.84	
Other	0.00	
Digital Health Technology	**%**	**Freq. (>0)**
Apple/Samsung/Huawei Health	18.67	42
Garmin Connect	3.11	7
Corona-Warn-App	19.11	43
Calorie Tracker App	12.00	27
Step Counter	10.22	23
Period Tracker	6.22	14
Calm	2.22	5
WebMD Symptom Checker	0.44	1
Sleep Tracker	9.78	22
Strava	6.67	15
Doctolib	8.89	20
Jameda	2.22	5
Healthline	0.44	1

15], we include this distinction for transparency without assigning theoretical weight in the discussion.

High Responsible Use. The revealed sufficient configuration for RU describes individuals who have a high level of eHL, EA, and CSE as peripheral conditions. A high level of ITM and a low level of TB towards digital health technologies have been identified as core conditions for these individuals to result in RU. They are individuals who critically assess digital health technologies, reflect on their use, and have confidence using them to engage in responsible use behavior. The absence of TB implies that critical skepticism enhances the capacity to evaluate technologies in a balanced, ethically sensitive manner. Rather than accepting technologies, it describes users who question implications and consider broader societal, environmental, and ethical dimensions of their use.

Low Responsible Use. The identified sufficient configuration for the negation of the outcome RU, i. e., low responsible use (~RU), describes individuals who have high levels of eHL, TB, and CSE as peripheral conditions. Further, they show low EA, which has been identified as a core condition, while the level of ITM is irrelevant for this condition. This configuration shows that technical skills and confidence alone do not ensure RU. Without EA, individuals fail to consider broader impacts. The presence of high TB in this configuration may promote uncritical use of digital health technologies, reducing awareness of potential harms, which might undermine responsible behavior. This configuration represents a competent but non-responsible user profile.

	Responsible Use	~Responsible Use
Configurations	C_RU	C_~RU
Electronic Health Literacy	•	•
IT-Mindfulness	●	
Trusting Beliefs	⊗	•
Ethical Awareness	•	⊗
Computer Self-efficacy	•	•
Raw coverage	0.40	0.42
Unique coverage	0.40	0.42
Consistency	0.90	0.90
Solution coverage	0.40	0.42
Solution consistency	0.90	0.90

Key: ● High level (i.e., presence) of a condition, ⊗ Low level (i.e., absence) of condition, ( ) ‘Do not care‘ situation (blank spaces), Large circles indicate core conditions, small circles indicate peripheral conditions.

Figure 2: Sufficient Configurations for Responsible and ~Responsible Use.

5 Discussion

This research identifies which configurations of ITM, eHL, TB, EA, and CSE are sufficient for high and low RU of digital health technologies. We interpret the two configurations and derive implications for theory and practice.

5.1 Understanding the Two User Types

The contrast between the two identified configurations sheds light on what differentiates responsible from non-responsible use. Both configurations share high levels of eHL and CSE, but differ in RU. They describe individuals who possess high eHL and CSE, yet differ in their outcomes. This suggests that technical competence, on its own, does not distinguish responsible from less responsible use. The critical differentiators between the configurations are EA and TB.

Type 1 users (critically engaged) combine low TB with high EA, creating a profile characterized by sustained critical evaluation of use consequences. Their low TB is consistent with a questioning stance toward technology outputs and implications. The presence of ITM then supports attentive engagement with features and failures rather than routine use. Consistent with prior work, responsible use requires active evaluation rather than passive reliance [56, 62].

Type 2 users (competent but uncritical) combine high TB with low EA, which creates a profile characterized by reliance on the

Table 3: Descriptive Statistics and Construct Reliability.

	Variable	M	SD	CR	CA	AVE	1	2	3	4	5	6
1	eHL	5.32	0.95	0.96	0.88	0.74	**0.86**					
2	EA	4.82	1.07	0.82	0.81	0.61	0.17	**0.78**				
3	ITM	4.43	1.33	0.90	0.87	0.69	0.29	-0.09	**0.83**			
4	TB	4.75	1.11	0.98	0.92	0.84	0.05	-0.26	0.50	**0.92**		
5	CSE	8.10	1.61	0.98	0.91	0.81	0.43	0.12	0.30	0.25	**0.90**	
6	RU	3.90	1.03	0.93	0.82	0.64	0.09	0.32	0.07	-0.26	0.03	**0.80**

Note: M = Mean; SD = Standard Deviation; CR = Composite Reliability; CA = Cronbach's Alpha; AVE = Average Variance Extracted. The square root of AVE is listed on the diagonal of bivariate correlations.

tool without ethical evaluation. They possess the same technical competencies as Type 1 users but use them with limited ethical scrutiny. High TB are consistent with reduced motivation to question outputs and implications, including the implicit assumption that providers have addressed ethical concerns.

This contrast aligns with the view that responsibility in digital contexts depends on how competencies, beliefs, and awareness combine in a given context and that it continuously needs to be enacted [13]. Further, high ethical awareness satisfies the epistemic condition of responsibility by ensuring that the user is not just acting, but is capable of answerability, meaning that they can explain why they used a tool and how it affects others [9]. Users cannot blindly rely on the algorithm or tool.

5.2 The Role of Trust

Our findings reveal a counterintuitive insight: low trust is associated with responsible use, whereas high trust leads to low responsible use. This suggests that critical skepticism is more conducive to responsible use than blind trust in digital health technologies. This pattern contrasts with established evidence that TB typically facilitates adoption and post-adoptive engagement [37, 7, 60]. We propose this difference stems from distinct goals. Adoption requires overcoming uncertainty about functionality, where trust reduces perceived risk and facilitates the use [5, 37]. Responsible use, however, requires sustained critical evaluation of impacts. In this context, trusting beliefs can reduce critical evaluation by increasing cognitive comfort and lowering users' motivation to question outputs and implications, potentially leading to misuse [20]. These patterns are consistent with a possible *critical-evaluation reduction* mechanism, whereby trusting beliefs shift users' attention away from independent evaluation and toward provider-assumed responsibility. In contrast, lower trusting beliefs are consistent with a questioning stance that maintains attention to potential harms and keeps ethical considerations salient, thereby supporting responsible use.

This finding suggests the need to re-conceptualize trust in technology contexts. The findings indicate that a dual-process model distinguishing *adoption-facilitating trusting beliefs* (focused on technology competence) from *responsibility-inhibiting trusting beliefs* (focused on technology benevolence without verification) might be necessary. In adoption contexts, trust helps users overcome initial uncertainty [37]. In responsible use contexts, however, trust creates complacency that prevents critical evaluation. Our results support shifting the perspective away from the notion that trust is universally beneficial, toward the recognition that it is context-dependent [25] and can potentially be detrimental for responsible use behavior. We suggest that the role of trusting beliefs should be investigated as a context-dependent factor which may support the adoption of digital health technologies, but hinder their responsible use. As trust in general is considered to be dynamic and multidimensional [25], initial trust in the adoption phase may change in the later stages of the technology use, when users may become aware of their full functionality and also possible implications.

The double-edged role of trust highlights a tension in digital responsibility. Optimizing for technology adoption through building trust may undermine the sustained commitment to critical evaluation necessary for responsible use, specifically, dependability [56]. Our findings suggest that in contexts requiring ethical judgment about indirect stakeholder impacts, the emphasis on building user trust may inadvertently create conditions that compromise the users' accountability (recognizing their role as agents whose actions impact others) and obligation (actively safeguarding against harms while promoting benefits) [56].

5.3 Theoretical Contributions

This study makes four theoretical contributions to IS research on technology use and the health context.

First, we theorize responsible use as a configurational outcome and provide exploratory evidence that it is associated with combinations of individual conditions rather than isolated net effects. By modeling equifinal and asymmetric configurations, we demonstrate how IT-specific traits, beliefs, and contextual competencies jointly relate to responsible use and its absence. This complements existing research using a configurational perspective to explain general IS use [39] by contributing that also configurations influence responsible use. This implies that configurations are central for understanding a range of different use patterns of the IS use lifecycle as well as responsible use. The moderate coverage values of the identified configurations are consistent with the scope of the study, as the demographically homogeneous sample of 62 participants and five theoretically selected conditions necessarily constrain the observable configuration space. The coverage values suggest that additional sufficient configurations, involving conditions not included in this study or underrepresented demographic groups, remain plausible and future research should examine broader samples and sets of conditions to map the full landscape of configurations that predispose responsible use.

Second, we contribute to digital responsibility research [13, 56] by adding an individual-level perspective and exploratory empirical evidence on how traits, beliefs, and competencies may relate to responsible-use patterns. Our results complement conceptual studies around digital responsibility by revealing which combinations of mindfulness, ethical awareness, literacy, self-efficacy, and trusting beliefs are sufficient for responsible use. This contribution grounds theoretical knowledge about digital responsibility in individual behavior and complements the predominant organizational-level examinations.

Third, we identify ethical awareness and trusting beliefs as boundary conditions that explain whether technical competencies are associated with responsible use. Specifically, high eHealth literacy and computer self-efficacy are present in the responsible and non-responsible configurations, which indicates that competence might be needed but is not enough to explain responsible use. Ethical awareness and trusting beliefs differentiate whether competence is accompanied by critical evaluation of consequences during use, and thus sharpens the theoretical arguments about when literacy-specific competencies result in responsible use [43].

Fourth, we propose the idea of *responsibility-inhibiting trusting beliefs* as a lens for future research on trust in normative post-adoptive settings. This distinction provides a theory-based explanation for why trusting beliefs can be beneficial for adoption, however, they can also be detrimental for responsible use.

5.4 Practical Implications

The findings also offer valuable implications for organizations, educators, and authorities that want to improve the responsible use of digital technologies. Organizations and educators seeking to promote responsible use of digital health technologies should implement specific interventions targeting the conditions distinguishing Type 1 from Type 2 users, and all three dimensions of digital responsibility: accountability, obligation, and dependability [56]. Accountability interventions aim to help users to recognize their role as agents whose actions impact others. While trust remains important for system adoption and use, the findings suggest that blind trust in digital health technologies may be negatively associated with their responsible use. Therefore, system designers and policymakers should balance promoting trust in these systems with encouraging healthy skepticism, for instance, with increasing system transparency and offering impact assessments of their systems, which supports requests for explainable systems, e. g., explainable artificial intelligence tools. Obligation interventions aim to equip users to actively safeguard against harms while enabling benefits. Programs that target responsible behavior in the context of digital health technologies, should not only primarily focus on teaching how to use tools, but also why and when to use them responsibly. This involves embedding ethical reflection and critical thinking into digital health education, e. g., by raising awareness about potential direct and indirect implications of digital technology use and actively fostering discourse about ethical, social, and environmental issues related to its use.

5.5 Limitations and Future Research

As with all empirical studies, the present research is subject to limitations that suggest future research directions. First, we acknowledge that our sample consists predominantly of young participants, as the age mainly ranges from 19 to 30 years, and male participants, limiting generalizability to other demographics and cultures, as responsible use may differ across age groups, genders, or cultural backgrounds. Future research should examine whether age, gender, and cultural background moderate the configurations we identified. Second, this study captures solely a point in time. Therefore, insights into the responsible use of digital health technology is limited to this snapshot in time. Longitudinal research could reveal how responsible use develops and whether users shift between types over time. Disruptive events such as data breaches or regulatory changes might alter the configurations, particularly the role of trusting beliefs. Tracking individuals across multiple technology adoptions could identify stable versus situational determinants. Third, while fsQCA identifies sufficient configurations, it does not indicate the unique contributions of individual variables to the outcome. Future research might combine configurational and linear approaches to build a comprehensive understanding of the drivers of responsible use. Finally, we did not examine actual responsible use behavior, only self-reported intentions, and the self-developed scale for RU relies on absolute formulations, which may increase susceptibility to social desirability bias in self-reported data. Future studies should complement self-reported measures with behavioral indicators and triangulate across multiple data sources, such as digital trace data or qualitative data, examining whether the identified configurations predict actual responsible use behavior such as privacy-protecting behaviors, verification of health information accuracy, and consideration of impacts on others.

6 Conclusion

This study explains responsible use of digital health technologies as a configurational outcome that is shaped by combinations of multiple factors. We use fsQCA and identify one configuration sufficient for responsible use and one configuration sufficient for low responsible use. In both configurations, technical competencies are present, which indicates that competence can be insufficient for responsible use unless it is accompanied by conditions that sustain critical evaluation during use. These findings offer an initial basis for refining theorizing about responsible use by showing how IT mindfulness, ethical awareness, trusting beliefs, eHealth literacy, and computer self-efficacy may jointly relate to responsible use.

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A Appendix

Table 4: Prior Work on Responsible Use and Related Concepts.

Concept	Reference	Context	Definition	Level of Analysis
Responsible use of AI	[51]	LLMs in telehealth	"[...] as using an AI system in a way that is ethical and trustworthy, contributing to the achievement of the intended goals for using the AI system." (p. 2127)	individuals, organizations
Responsible use of AI	[65]	AI for decision-making	"[...] to employ AI technology responsibly to avoid and minimize any potential or unintended risks." (p. 2)	individuals, organizations
Eco-responsible use of technologies	[2]	Education	According to them, eco-responsible use involves awareness of the environmental consequences of digital technology use, using such technologies in ways that support sustainable development and contribute to the health of the planet, and developing a critical and responsible perspective toward digital technologies.	individuals
Responsible social media use	[8]	Social Media	"The legally, morally, and socially mindful engagement with social media considering the impact on oneself, and the broader world." (p. 10)	individuals
Green use of digital technologies	[29]	Technology consumption behavior	"Green use is defined as the responsible use of computers, from turning off computers when they are not in use, to using blank screensavers, or putting computers in hibernation or sleep mode." (p. 6)	individuals
Responsible use of digital technologies	This study; based on [13, 9, 56, 69]	Digital health	[...] responsible use of technologies as a pattern of use in which individuals critically reflect on consequences and adjust their use to reduce potential harms and support potential benefits for stakeholders	individuals

Table 5: Overview of Validation Measures.

Validity	Validation
Design validity	Constructs are based on established constructs in literature. The sample size is adequate for the type of analysis [34]. There is no evidence of common method bias.
Measurement validity	Indicator and construct reliability, as well as discriminant validity, are all given. The results remain stable when calibration anchors and frequency thresholds are adjusted [46].
Inferential validity	The findings are robust and reliable, supported by high consistency scores [57].