Public Readiness for a Personalized Digital Health Platform in Bavaria (10P-Health): A Cross-Sectional Survey of Operational, Legal, Technological, and Stakeholder Determinants of Perceived Feasibility

Public Readiness for 10P-Health Platform in Bavaria

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DOI: 10.25929/pf1mz879

ABSTRACT

Background: Digital health technologies and artificial intelligence (AI) are shifting healthcare from reactive treatment toward predictive and personalized care. The 10P-Health framework extends earlier P-models through ten principles: Predictive, Preventive, Personalized/Precision, Participatory, Pertinent, Proactive, Privacy-preserving, Pervasive, Permanent, and Platform-based. Public readiness for such a framework in Bavaria has not been established.

Objective: This study assessed public readiness for the 10P-Health framework in Bavaria and examined whether operational readiness (OR), legal and regulatory requirements (LRR), stakeholder engagement (SE), and technological infrastructure (TI) predict its perceived feasibility.

Methods: A cross-sectional survey of 200 adult residents of Bavaria was conducted using an online questionnaire. All constructs were measured with five-point Likert scales. Data were analyzed with descriptive statistics, reliability analysis, principal component analysis, Pearson correlations, and multiple linear regression.

Results: Respondents were predominantly young and well-educated, and 77.5% had previously used a digital health platform, medical device, or health-related application. All constructs showed acceptable internal consistency (Cronbach's alpha = .706–.768). Perceived feasibility correlated significantly with all four predictors. The regression model explained 57.7% of the variance in perceived feasibility. TI (β = .402, $p < .001$), OR (β =.330, $p < .001$), and SE (β = .207, p = .001) were significant predictors, whereas LRR was not (β = .029, p = .614). Resource adequacy and provider preparedness received the lowest ratings.

Conclusions: The findings indicate moderate readiness among a predominantly young, highly educated, and digitally experienced sample. Perceived feasibility was associated primarily with technological infrastructure, operational readiness, and stakeholder engagement, whereas legal requirements appeared to function as a background condition rather than a direct driver.

KEYWORDS

AI in health, personalized medicine, patient attitudes, public readiness, 10P-Health

1. Introduction

1.1. Background

Healthcare is shifting from reactive treatment toward proactive, predictive, and personalized care, driven by advances in artificial intelligence (AI) and digital health [1,2]. This transition has been shaped by the gradual evolution of personalized-medicine paradigms. The P4 medicine model presented predictive, preventive, personalized, and participatory, articulated by Hood and Galas [3]. Subsequent models proposed a P5 medicine that adds the psycho-cognitive dimension proposed by Gorini and Pravettoni [4], and the model was later broadened to a 6P framework incorporating the additional dimension of public health [5]. The framework was subsequently expanded to a P9 concept of healthcare, encompassing personalized, predictive, preventive, participatory, pervasive, precise, privacy-preserving, protective, and priced-reasonably dimensions [6].

Building on this trajectory, Chaltikyan [7] (G. Chaltikyan, personal communication, November 14, 2019) describes 10P-Health, which extends earlier P-models through ten principles: Predictive, Preventive, Personalized/Precision, Participatory, Pertinent, Proactive, Privacy-preserving, Pervasive, Permanent, and Platform-based. The 10P-Health framework reflects the convergence of personalized medicine with digital health, big data, and AI. Rather than prescribing a fixed implementation pathway, it emphasizes the integration of multimodal data, the use of digital health applications, continuous monitoring, the application of AI and predictive analytics. Its orientation remains patient-centered, seeking to enable more effective disease management and timely interventions while stressing on continuity of care beyond clinical encounter, patient inclusion, interoperability, and platform-based infrastructure that can support long-term, precision-oriented care.

1.2 The Bavarian Context

Despite global progress, healthcare systems have faced difficulties in adopting data-intensive and AI-driven models, particularly in relation to technological readiness, regulatory constraints, and infrastructure [8]. Bavaria is one of the most financially developed regions in Germany [9], and its health and care economy represents a major share of the state's economic output and employment [10]. Bavarian institutions have access to high-quality patient care and advanced medical research, but the transformation toward personalized interventions, real-time monitoring, and AI-driven analytics is still in its early stages.

Operational readiness in this context reflects preparedness to scale up digital health platforms, data-sharing mechanisms, and AI-driven health technology [11]. Effective integration of a 10P-Health framework requires a robust technical infrastructure capable of integrating multimodal health data sources, including omics, internet of things (IoT), imaging, and electronic health records (EHR). Data silos and technological barriers often fragment systems and hinder timely, personalized care [12]. Training practitioners to work with AI-based decision tools is important because AI complements medical expertise [13], and improving patient digital literacy is equally necessary for informed engagement with digital tools [14]. Without fundamental digital competencies, patients struggle to benefit from personalized technologies, which can widen health disparities [15].

Bavaria's digital health transition is also shaped by a multi-layered regulatory environment. AI-driven healthcare must respect patient rights, ethics, and data protection law [16]. The European Health Data

Space (EHDS) aims to foster secure health data exchange across European Union member states while empowering patients with greater control over their data [17], yet its integration requires navigation of overlapping frameworks including the General Data Protection Regulation (GDPR), the Federal Data Protection Act (BDSG), and the Bavarian Data Protection Act (BayDSG). Additional national frameworks relevant to digital health include the Digital Act (DigiG), the Health Data Use Act (GDNG), the Digital Healthcare Act (DVG), and the Medical Device Regulation (MDR). Strict privacy safeguards such as those in the GDPR are required to balance patient confidentiality with data accessibility. At the same time, Bavaria supports AI in healthcare through initiatives within the High-Tech Agenda Bavaria and centers such as BayernKI, which promote digital health platforms, telemedicine, and AI-powered diagnostics.

1.3. Problem Statement

Personalized health offers advantages that elevate patients' overall care. Yet realizing such an approach and adopting a comprehensive model such as the 10P-Health framework in the Bavarian healthcare system remains uncertain. This uncertainty arises from concerns about technological infrastructure, stakeholder engagement, regulatory and legal compliance, and operational readiness. Integrating personalized health platforms requires investment in digital systems, workforce training, and AI-powered solutions to ensure smooth adoption; without a clear assessment of these elements, resistance to change, data silos, and inefficiencies could hinder implementation. Complex regulations add further difficulty, as a personalized platform must meet strict legal requirements while maintaining data security and patient privacy. Stakeholder engagement is equally important, since issues of trust, acceptance, and awareness of AI-based solutions have produced resistance to change. It also remains unclear whether Bavaria's technical capabilities are sufficient to support real-time tracking, system integration, and large-scale, device-agnostic health data.

Patients' perceptions, trust, and attitudes toward AI-based health platforms need to be assessed, as these factors strongly influence their adoption and sustained use. Understanding these perceptions is therefore necessary to inform an ethically sound, legally compliant, and patient-centered digital transition. This study addresses these gaps by using a quantitative survey to evaluate public readiness and to examine the factors associated with the perceived feasibility of implementing a personalized 10P-Health framework in Bavaria.

1.4 Aim and Objectives

This study assessed the feasibility of implementing the 10P-Health framework in Bavaria from the perspective of adult residents, evaluating four factors: operational readiness, legal and regulatory requirements, stakeholder engagement, and technological infrastructure. The objectives were:
1 – Assess the level of operational readiness required, including infrastructure, workforce, and resource availability in Bavaria.
2 – Identify perceptions of the legal and regulatory requirements related to healthcare data, patient privacy, and adherence to Bavarian, German, and EU laws.
3 – Evaluate the role of stakeholder engagement.
4 – Investigate perceptions of the technological infrastructure required to support the scalability in Bavaria.

2. Methods

2.1 Study Design

This study used a quantitative, cross-sectional survey design. The survey collected statistically analyzable, comparable, and measurable data on patient attitudes toward digital health technologies, AI-driven care, and data sharing.

2.2 Setting and Participants

The study was conducted in the German federal state of Bavaria. Eligible participants were adults (18 years or older) residing in Bavaria, representing a range of digital health experiences. On the consent page, respondents confirmed that they were at least 18 years old before starting the questionnaire, and residence was recorded through a required question on region of residence within Bavaria. The number of completed responses obtained was 200, with no missing values on any analyzed variable, because every questionnaire item required an answer before the form could be submitted. The survey administration period was June until August 2025.

2.3 Recruitment

Participants were recruited through non-probability convenience sampling. Data were collected through an anonymous, bilingual (German and English) questionnaire hosted on Google Forms, which took about 10 minutes to complete and required no login or personal details. To broaden outreach beyond online channels and to include people with different educational backgrounds and levels of digital skill, a bilingual flyer in English and German was developed, printed, and handed out in person in selected regions of Bavaria, specifically Pfarrkirchen, Munich, and Erlangen. The flyer carried a QR code linking to the questionnaire, and people who were less familiar with digital tools could complete the questionnaire with assistance from a member of the research team. Internal distribution was additionally facilitated through a professional network in Munich. Recruitment was further supported by email communication with multiple organizations, including elderly care facilities and community-based associations, inviting their members to participate. Despite these measures, the final sample remained predominantly young and highly educated (Section 3.1); the implications are discussed in Section 5.
Because the questionnaire was distributed through an open link, printed flyers, and partner organizations, the number of people who received the invitation is unknown, and a response rate could not be calculated. Google Forms records only submitted responses, so partially completed questionnaires were not captured. A total of 200 complete responses were received during the survey period.

2.4 Questionnaire and Measures

All 21 construct items were developed de novo for this study, based on the literature on personalized medicine, digital health readiness, data protection, and stakeholder engagement reviewed in Section 1, rather than adapted from existing validated scales. Responses were measured as levels of agreement or disagreement with a series of statements, using five-point Likert scales ranging from 1 to 5, with higher values indicating stronger agreement.

The instrument comprised three parts. The first part collected demographic characteristics: age group, gender, highest level of education, and region of residence within Bavaria. The second part assessed digital health background: self-rated familiarity with digital health technologies, previous use of a digital health platform, medical device, or health-related application, the presence of chronic health conditions, and frequency of use of six categories of digital health services or tools (telemedicine consultations or virtual doctor visits, fitness and wellness applications, remote monitoring devices or applications, medication reminders or appointment scheduling tools, patient portals, and online symptom checkers or chat-based health services).

The third part measured five constructs using 21 Likert-scale items. Operational Readiness (OR) comprised four items covering the adequacy of system resources such as funding, trained staff, and technical infrastructure; the monitoring and improvement of digital health services; the training and comfort of healthcare professionals with digital tools; and willingness to pay a reasonable amount for personalized digital health services.

Legal and Regulatory Requirements (LRR) comprised four items covering trust that certified platforms protect data privacy and security; clarity of information about how health data is collected, used, and shared; ease of giving or withdrawing consent; and confidence in current laws and regulations such as the GDPR.

Stakeholder Engagement (SE) comprised four items covering whether digital health tools are designed with patients' needs in mind and incorporate patient feedback; whether patients and citizens should be consulted when new digital health services are developed; trust in digital health systems and AI-generated recommendations when supervised by medical professionals; and whether digital health services should be accessible and inclusive regardless of income, disability, language, or digital skills.

Technological Infrastructure (TI) comprises four items covering seamless sharing of health records among treating doctors or clinics; reliable access to internet or mobile networks; smooth interoperability of digital systems and applications used in healthcare; and openness to digital tools that use AI and analytics to help predict or prevent health problems.

Feasibility of Implementing a Health Platform (FIHP) comprises five items covering whether using a personalized digital health platform seems practical and achievable; whether such a platform could be integrated into daily routine without major disruption; whether the healthcare providers and institutions used by the respondent are prepared to support personalized digital health services; whether certified personalized platforms should be supported long-term; and whether the benefits of a personalized platform will outweigh the costs and risks. FIHP was treated as the dependent variable. OR, LRR, SE, and TI were treated as independent variables, and the construct scores were computed as the mean of their constituent items, with each item weighted equally.

2.5 Ethical Considerations

All participants provided informed consent prior to data collection, ensuring their awareness of the purpose and procedures of the study and of their right to withdraw at any time without consequence. Privacy and anonymity were maintained, with survey responses securely stored and anonymized to prevent the identification of participants. The research complied with the GDPR and other applicable data protection laws. Data integrity and researcher neutrality were maintained by avoiding leading questions and any form of pressure on respondents.

2.6 Statistical Analysis

Data were analyzed using IBM SPSS Statistics (Version 31.0.0.0; IBM Corp.) [18]. Demographic and digital health background variables were summarized using frequencies and percentages. Construct items were summarized using means, standard deviations, minimum, and maximum values.

The distribution of each construct item was examined using the Kolmogorov-Smirnov test with Lilliefors significance correction. Internal consistency was assessed for each construct using Cronbach's alpha, with .70 applied as the acceptable threshold. The suitability of the data for factor analysis was examined using the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy and Bartlett's test of sphericity. Principal component analysis with varimax rotation and Kaiser normalization was then performed on the 21 construct items, with a fixed five-factor solution. Composite reliability (CR) and average variance extracted (AVE) were calculated for each construct, with .50 applied as the benchmark for AVE.

Relationships among constructs were examined using Pearson correlation coefficients with two-tailed significance tests. Multiple linear regression was conducted with FIHP as the dependent variable and OR, LRR, SE, and TI entered simultaneously. Multicollinearity was assessed with tolerance and variance inflation factor (VIF) values derived from the correlations among the predictors (Table 9), with VIF values below 5 taken to indicate no problematic collinearity. Although the item distributions departed from normality, the normality assumption of linear regression concerns the residuals rather than the individual items, and least-squares estimates and their confidence intervals remain valid without normally distributed data in sufficiently large samples, often fewer than 100 observations [19]. Ordinary least-squares regression was therefore retained, and 95% confidence intervals for the regression coefficients are reported. Statistical significance was set at $p < .05$.

3. Results

3.1 Participant Characteristics

Table 1 presents respondents' demographic characteristics. Most respondents were under 35 years old, including 50.0% aged 25–34 and 16.5% under 25. The remaining respondents were aged 35–44 (16.0%), 45–54 (8.5%), or 55 and above (9.0%). Females accounted for 59.5% of the sample, males for 40.0%, and 0.5% preferred not to state their gender. Regarding education, 38.0% held a Master's degree or equivalent and 33.0% held a Bachelor's degree, while 14.5% reported a high-school diploma, 10.5% an apprenticeship or technical certificate, and 3.0% a doctorate. Geographically, 43.5% of respondents were located in Lower Bavaria and 36.0% in Upper Bavaria, with the remaining regions each accounting for 7.0% or less.

Characteristic	Category	n	%
Age group	Under 25	33	16.5
	25–34 years	100	50.0
	35–44 years	32	16.0
	45–54 years	17	8.5
	55 years and above	18	9.0
Gender	Female	119	59.5
	Male	80	40.0
	Prefer not to say	1	0.5
Highest level of education	High-school diploma	29	14.5
	Apprenticeship or technical certificate	21	10.5
	Bachelor's degree	66	33.0
	Master's or equivalent	76	38.0
	Doctorate / PhD / MD	6	3.0
	Prefer not to say	2	1.0
Region in Bavaria	Lower Bavaria	87	43.5
	Upper Bavaria	72	36.0
	Upper Palatinate	14	7.0
	Middle Franconia	10	5.0
	Lower Franconia	7	3.5
	Swabia	7	3.5
	Upper Franconia	3	1.5

Table 1: Demographic Characteristics of Survey Respondents (N = 200).

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3.2 Digital Health Background and Service Use

Self-rated familiarity with digital health technologies and prior use of digital health services are presented in Table 2. Of the respondents, 34.0% reported being somewhat familiar and 17.5% very familiar with digital health technologies, while 25.0% were neutral, 17.0% slightly familiar, and 6.5% not familiar at all. Previous use of a digital health platform, medical device, or health-related application was reported by 77.5% of respondents. Chronic health conditions were reported by 28.5% of respondents.
Frequency of use varied across service types (Table 2). Fitness and wellness applications showed the highest engagement, with 34.5% of respondents using them regularly and 23.5% often, and only 15.5% never using them. Telemedicine consultations showed limited adoption, with 47.5% never using them

and 2.0% using them regularly. Remote monitoring devices or applications were never used by 54.5% of respondents, and medication reminders or appointment scheduling tools by 44.5%. Patient portals and online symptom checkers were never used by 33.0% and 40.0% of respondents, respectively.

Item	Category	n	%
Familiarity with digital health technologies	Not familiar at all	13	6.5
	Slightly familiar	34	17.0
	Neutral	50	25.0
	Somewhat familiar	68	34.0
	Very familiar	35	17.5
Ever used a digital health platform, medical device, or application	No	45	22.5
	Yes	155	77.5
Chronic health condition	No	143	71.5
	Yes	57	28.5
Telemedicine consultations or virtual doctor	Never	95	47.5
	Rarely	49	24.5
	Sometimes	37	18.5
	Often	15	7.5
	Regularly	4	2.0
Fitness and wellness apps	Never	31	15.5
	Rarely	24	12.0
	Sometimes	29	14.5
	Often	47	23.5
	Regularly	69	34.5
Remote monitoring devices/apps	Never	109	54.5
	Rarely	43	21.5
	Sometimes	27	13.5
	Often	13	6.5
	Regularly	8	4.0
Medication reminders or appointment scheduling tools	Never	89	44.5
	Rarely	32	16.0
	Sometimes	30	15.0
	Often	19	9.5
	Regularly	30	15.0
Patient portals	Never	66	33.0
	Rarely	58	29.0
	Sometimes	39	19.5
	Often	22	11.0
	Regularly	15	7.5
Online symptom checkers or chat-based health services	Never	80	40.0
	Rarely	49	24.5
	Sometimes	31	15.5
	Often	21	10.5
	Regularly	19	9.5

Table 2: Familiarity With Digital Health Technologies and Frequency of Use of Digital Health Services (N = 200).

3.3 Descriptive Statistics for Construct Items

Item-level descriptive statistics are presented in Table 3. All 21 items used the full response range from 1 to 5. Within Operational Readiness, the adequacy of system resources received the lowest mean of all items (M = 2.73, SD = 0.84), followed by the training and comfort of healthcare professionals with digital tools (M = 2.97, SD = 1.02). Within Legal and Regulatory Requirements, item means ranged from 3.15 (SD = 1.25) for clarity of information about data collection and use to 3.41 (SD = 1.21) for trust in certified platforms. Within Stakeholder Engagement, accessibility and inclusiveness received the highest mean of all items (M = 4.58, SD = 0.80), followed by consultation of patients and citizens (M = 4.25, SD = 0.93). Within Technological Infrastructure, item means ranged from 3.97 (SD = 1.14) to 4.28 (SD = 0.95). Within Feasibility of Implementing a Health Platform, provider preparedness received a mean of 2.75 (SD = 0.94), while long-term support of certified platforms received a mean of 4.20 (SD = 0.88).

Construct	Item	Min	Max	M	SD
OR	The Bavarian healthcare system has enough resources, such as funding, trained staff, and technical infrastructure	1	5	2.73	0.84
	Digital health services will be regularly monitored and improved to ensure quality	1	5	3.20	0.96
	Healthcare professionals I interact with are well trained and comfortable using digital health tools	1	5	2.97	1.02
	I am willing to pay a reasonable amount for personalized digital health services that clearly benefit my health care	1	5	3.26	1.17
LRR	I trust that certified digital health platforms will protect my data privacy and security	1	5	3.41	1.21
	I am clearly informed about how my health data is collected, used, and shared	1	5	3.15	1.25
	When I use digital health apps or platforms, I can easily give or withdraw my consent	1	5	3.39	1.04
	Current laws and regulations (e.g., GDPR) protect my rights in digital healthcare	1	5	3.37	0.99
SE	Digital health tools are designed with patients' needs in mind and incorporate patient feedback	1	5	3.11	0.94
	Patients and citizens should be consulted when new digital health services are developed	1	5	4.25	0.93
	I trust digital health systems and AI-generated health recommendations when supervised by medical professionals	1	5	3.62	1.09
	Digital health services should be accessible and inclusive, regardless of income, disability, or language	1	5	4.58	0.80
TI	My health records should be shared seamlessly among the doctors or clinics involved in my care	1	5	4.13	1.07
	I have reliable access to internet or mobile networks needed to use digital health services	1	5	4.28	0.95
	Digital systems and apps used in healthcare should work smoothly together	1	5	4.17	1.08
	I am open to digital tools that use AI and analytics to help predict or prevent health problems	1	5	3.97	1.14
FIHP	Using a personalized digital health platform for my own care seems practical and achievable	1	5	3.77	1.06
	I could integrate such a platform into my routine without major disruption	1	5	3.86	0.90
	The healthcare providers and institutions I use are prepared to support personalized digital health services	1	5	2.75	0.94
	Certified personalized digital health platforms should be supported long-term	1	5	4.20	0.88
	The benefits of a personalized digital health platform will outweigh the costs and risks	1	5	3.65	0.94

Table 3: Descriptive Statistics for Construct Items (N = 200).

Note. OR = Operational Readiness; LRR = Legal and Regulatory Requirements; SE = Stakeholder Engagement; TI = Technological Infrastructure; FIHP = Feasibility of Implementing a Health Platform.

Construct-level scores are presented in Table 4. TI recorded the highest mean (M = 4.14, SD = 0.81), followed by SE (M = 3.89, SD = 0.64), FIHP (M = 3.64, SD = 0.68), LRR (M = 3.33, SD = 0.85), and OR (M = 3.04, SD = 0.62).

Construct	Min	Max	M	SD
Operational Readiness (OR)	1.50	5.00	3.04	0.62
Legal and Regulatory Requirements (LRR)	1.00	5.00	3.33	0.85
Stakeholder Engagement (SE)	1.75	5.00	3.89	0.64
Technological Infrastructure (TI)	1.25	5.00	4.14	0.81
Feasibility of Implementing a Health Platform (FIHP)	1.20	5.00	3.64	0.68

Table 4: Descriptive Statistics for Construct Scores (N = 200).

3.4 Normality

Results of the Kolmogorov-Smirnov test are presented in Table 5. All 21 items deviated significantly from a normal distribution ($p < .001$ in every case). Test statistics ranged from 0.169 to 0.261 for the OR and LRR items, from 0.211 to 0.429 for the SE items, from 0.237 to 0.315 for the TI items, and from 0.210 to 0.270 for the FIHP items. The largest deviation was observed for SE4 (0.429).

Item	Statistic	df	Sig.	Item	Statistic	df	Sig.
OR1	0.261	200	< .001	SE3	0.281	200	< .001
OR2	0.225	200	< .001	SE4	0.429	200	< .001
OR3	0.194	200	< .001	TI1	0.274	200	< .001
OR4	0.242	200	< .001	TI2	0.315	200	< .001
LRR1	0.223	200	< .001	TI3	0.298	200	< .001
LRR2	0.169	200	< .001	TI4	0.237	200	< .001
LRR3	0.186	200	< .001	FIHP1	0.241	200	< .001
LRR4	0.192	200	< .001	FIHP2	0.262	200	< .001
SE1	0.211	200	< .001	FIHP3	0.220	200	< .001
SE2	0.285	200	< .001	FIHP4	0.270	200	< .001
FIHP5	0.210	200	< .001				

Table 5: Kolmogorov–Smirnov Test of Normality (N = 200).

3.5 Reliability

Internal consistency results are presented in Table 6. All five constructs exceeded the .70 threshold. Cronbach's alpha was .768 for OR, .747 for LRR, .706 for SE, .762 for TI, and .763 for FIHP.

Construct	No. of items	M	SD	Cronbach's α
Operational Readiness (OR)	4	3.04	0.62	.768
Legal and Regulatory Requirements (LRR)	4	3.33	0.85	.747
Stakeholder Engagement (SE)	4	3.89	0.64	.706
Technological Infrastructure (TI)	4	4.14	0.81	.762
Feasibility of Implementing a Health Platform (FIHP)	5	3.64	0.68	.763

Table 6: Internal Consistency of Constructs (N = 200).

3.6 Factor Analysis

The KMO measure of sampling adequacy was .854, and Bartlett's test of sphericity was significant, $\chi^2(210) = 1532.884$, $p < .001$ (Table 7).

Measure	Value
Kaiser-Meyer-Olkin measure of sampling adequacy	.854
Bartlett's test of sphericity: approx. χ^2	1532.884
df	210
Sig.	< .001

Table 7: KMO and Bartlett's Test.

Principal component analysis with varimax rotation produced a five-component solution. The five retained components had initial eigenvalues of 6.615, 1.976, 1.485, 1.149, and 1.046, together explaining 58.432% of the total variance. After rotation, the components accounted for 15.029%, 12.500%, 12.110%, 9.511%, and 9.283% of variance, respectively.

Rotated factor loadings, CR, and AVE values are presented in Table 8. CR values exceeded .70 for all constructs: OR (CR = .767), LRR (CR = .791), SE (CR = .722), TI (CR = .757), and FIHP (CR = .720). AVE values were below the .50 benchmark for all of the five constructs: LRR (AVE = .490), OR (AVE = .456), TI (AVE = .439), SE (AVE = .407), and FIHP (AVE = .341). The lowest individual loadings were observed for SE1 (.403) and FIHP3 (.480).

Construct	Item	Loading	CR	AVE
Operational Readiness (OR)	OR1	.785	.767	.456
	OR2	.614		
	OR3	.556		
	OR4	.721		
Legal and Regulatory Requirements (LRR)	LRR1	.626	.791	.490
	LRR2	.794		
	LRR3	.629		
	LRR4	.734		
Stakeholder Engagement (SE)	SE1	.403	.722	.407
	SE2	.698		
	SE3	.579		
	SE4	.803		
Technological Infrastructure (TI)	TI1	.700	.757	.439
	TI2	.568		
	TI3	.679		
	TI4	.695		
Feasibility of Implementing a Health Platform (FIHP)	FIHP1	.594	.720	.341
	FIHP2	.600		
	FIHP3	.480		
	FIHP4	.617		
	FIHP5	.618		

Table 8: Rotated Factor Loadings, Composite Reliability, and Average Variance Extracted.

3.7 Correlation Analysis

Pearson correlations among the five constructs are presented in Table 9. All correlations were positive and statistically significant at the .01 level. FIHP correlated most strongly with TI ($r = .649$, $p < .001$), followed by SE ($r = .585$, $p < .001$), OR ($r = .550$, $p < .001$), and LRR ($r = .462$, $p < .001$). Among the independent constructs, the strongest association was between SE and TI ($r = .606$, $p < .001$), followed by LRR with TI ($r = .483$, $p < .001$) and LRR with OR ($r = .460$, $p < .001$).

The weakest association was between OR and TI ($r = .324$, $p < .001$).

Construct	FIHP	OR	LRR	SE	TI
FIHP	1				
OR	.550**	1			
LRR	.462**	.460**	1		
SE	.585**	.368**	.420**	1	
TI	.649**	.324**	.483**	.606**	1

Table 9: Pearson Correlations Among Constructs (N = 200).

Note. ** Correlation is significant at the .01 level (two-tailed).

3.8 Regression Analysis

Results of the multiple linear regression are presented in Table 10. The model produced a multiple correlation of $R = .760$, with $R^2 = .577$ and adjusted $R^2 = .569$, and a standard error of the estimate of 0.444. The overall model was significant, $F(4, 195) = 66.554$, $p < .001$, with a regression sum of squares of 52.464 and a residual sum of squares of 38.429 out of a total of 90.893.

Three of the four predictors were significant. TI recorded the largest standardized coefficient ($\beta = .402$, $t = 6.513$, $p < .001$), followed by OR ($\beta = .330$, $t = 6.150$, $p < .001$) and SE ($\beta = .207$, $t = 3.426$, $p = .001$). LRR was not a significant predictor ($\beta = .029$, $t = 0.504$, $p = .614$). The constant was not significant ($B = 0.240$, $t = 1.100$, $p = .273$).

Tolerance values ranged from .57 to .75 and VIF values from 1.33 to 1.76, well below the threshold of 5, indicating no problematic multicollinearity among the predictors (Table 10). The 95% confidence intervals for the coefficients of TI, OR, and SE did not include zero, whereas the interval for LRR did (Table 10).

Predictor	B	SE B	β	t	p	95% CI for B	Tolerance	VIF
(Constant)	0.240	0.218		1.100	.273	[−0.190, 0.670]		
Operational Readiness (OR)	0.359	0.058	.330	6.150	< .001	[0.245, 0.473]	.75	1.33
Legal and Regulatory Requirements (LRR)	0.023	0.046	.029	0.504	.614	[−0.068, 0.114]	.66	1.52
Stakeholder Engagement (SE)	0.218	0.064	.207	3.426	.001	[0.092, 0.344]	.59	1.69
Technological Infrastructure (TI)	0.336	0.052	.402	6.513	< .001	[0.233, 0.439]	.57	1.76

Table 10: Multiple Linear Regression Predicting Feasibility of Implementing a Health Platform (N = 200).

Note. B = unstandardized coefficient; SE B = standard error of B; β = standardized coefficient; CI = confidence interval; VIF = variance inflation factor. Tolerance and VIF were derived from the correlations among the predictors (Table 9).

4. Discussion

4.1 Overview of Findings

This survey assessed readiness for the 10P-Health platform among adult residents of Bavaria and examined the factors associated with its perceived feasibility. Respondents were predominantly young highly educated, reported broad prior exposure to digital health, and perceived feasibility was moderate overall. The regression model explained a substantial share of the variance in perceived feasibility, with technological infrastructure, operational readiness, and stakeholder engagement emerging as significant predictors and legal and regulatory requirements not reaching significance. The pattern of responses indicates a divergence between confidence in technological and personal capacity, and confidence in institutional capacity.

4.2 Operational Readiness and Institutional Capacity

Operational readiness received the lowest overall assessment among the constructs, with concerns particularly evident regarding system resources, including funding, trained staff, and technical infrastructure. Perceived training and comfort of healthcare professionals with digital tools were also relatively low, while provider preparedness showed a similarly limited assessment. Despite these reservations, operational readiness emerged as the second strongest predictor of perceived feasibility, indicating that respondents linked the feasibility of personalized digital health implementation closely to institutional capacity even while perceiving that capacity as limited.

These perceptions can be read against the broader context described in the literature. The German digital health market has continued to expand in recent years, providing a favorable macroeconomic backdrop. However, regional infrastructure gaps, including incomplete 5G coverage in rural areas, may constrain scalability [20], while regulatory complexity in a multi-stakeholder environment may further limit the scalability of digital health solutions [21]. Concerns regarding staff competence are consistent with arguments that digital health adoption depends on upskilling doctors, nurses, data scientists, and IT specialists [22], embedding AI literacy into medical education [23], and ensuring the availability of cybersecurity specialists, AI engineers, and compliance officers [24]. The GDPR requirement to appoint data protection officers further underlines the need for specialized governance expertise [25,26].

Notably, respondents demonstrated greater willingness to pay a reasonable amount for personalized digital health services than the level of confidence expressed regarding system resources and staff competence. This suggests that respondents' openness to adoption may not represent the principal constraint identified by respondents; rather, institutional capacity and workforce preparedness appear to represent more significant barriers.

4.3 Legal and Regulatory Requirements

Legal and regulatory requirements received a moderate overall assessment. Respondents expressed broadly similar levels of trust in the ability of certified platforms to protect data privacy and security, confidence in the protection afforded by existing laws such as the GDPR, and the perceived ease of giving or withdrawing consent. In contrast, clarity regarding how health data are collected, used, and shared received the weakest assessment within this construct. This pattern suggests that respondents place greater confidence in the existence of formal legal protections than in the transparency of everyday data practices.

The literature offers a consistent account of this gap. The GDPR establishes clear requirements concerning consent, data minimization, and pseudonymization or anonymization [27,28], while the BDSG reinforces patient rights relating to rectification and erasure [29]. The Patient Data Protection Act allows patients to make EHR available for research where they provide explicit consent [30]. At the same time, meeting these formal requirements does not by itself guarantee that data practices are

transparent to patients, as data protection impact assessments intended to mitigate such risks are not uniformly standardized at the clinical level [31].

The finding suggests that respondents view regulation primarily as a necessary background condition. Legal safeguards nevertheless remain important to adoption, since AI-driven healthcare must meet requirements relating to patient rights, ethics, and data protection, while questions concerning liability for AI-assisted decisions remain unresolved under German law [32]. Depending on their intended use, healthcare AI systems may also be subject to additional regulatory requirements concerning explainability, bias mitigation, and ongoing auditing.

4.4 Stakeholder Engagement and Trust

Stakeholder engagement received one of the strongest overall assessments and included the highest-rated item in the survey. Respondents strongly endorsed the principle that digital health services should be accessible and inclusive regardless of income, disability, or language, and supported the involvement of patients and citizens in the development of new services. Trust in digital health systems and AI-generated recommendations was more moderate and appeared conditional on appropriate supervision by medical professionals. At the same time, respondents expressed comparatively less confidence that existing digital health tools are adequately designed around patients' needs and incorporate patient feedback. This indicates a perceived gap between the participatory principles that respondents endorse and the patient-centeredness of currently available tools.

Stakeholder engagement was also positively associated with perceived feasibility and showed a strong relationship with technological infrastructure. These findings align with accounts describing trust as a prerequisite for digital health adoption rather than merely an influencing factor, with trust anchored in confidentiality, physician endorsement, and confidence in the healthcare system. Policy frameworks are relevant in this context: the Digital Healthcare Act has institutionalized reimbursement for digital health applications [33], while the Bavarian State Ministry of Health and Care acts as both regulator and strategic investor in digital health innovation [34]. Preparedness among future clinicians is also relevant: a survey of first-year medical students at two Munich universities found that two-thirds did not feel well informed about AI in medicine, and only just over half considered AI to have useful medical applications, most often in drug research and development rather than in clinical use [35]. Together with the conditional nature of respondents' trust in AI, these findings suggest that physician oversight and participatory design are important conditions for public acceptance of digital health technologies.

4.5 Technological Infrastructure

Technological infrastructure received the strongest overall assessment and emerged as the most important predictor of perceived feasibility. Respondents expressed confidence in access to internet and mobile networks, strongly endorsed the seamless sharing of health records among treating clinicians, and supported interoperability between digital systems and applications. Openness to AI and analytics for prediction or prevention was also favorable, although responses were more varied than those concerning connectivity and interoperability. This suggests that respondents may be more consistently comfortable with the foundational infrastructure required for digital health than with the application of AI-based tools.

Two features of these findings warrant attention. First, several of the most highly rated infrastructure items are expressed as expectations or requirements rather than direct descriptions of current provision. Consequently, positive assessments may reflect what respondents consider necessary for effective digital health implementation as much as what they currently experience. Second, respondents' confidence in their own connectivity contrasts with reported connectivity gaps in rural areas of Bavaria [20,36] and with observations that rural settings may face slower systems and more limited AI acceptance. Interoperability nevertheless remains a documented constraint, international standards such as HL7, DICOM, and FHIR are considered central to secure data sharing between providers and AI systems,

yet Germany's federated healthcare structure complicates integration [37], while fragmentation across federal states can hinder interoperability and data exchange [38]. Investment costs may also limit adoption, particularly among small and medium-sized healthcare organizations.

5. Limitations

Several limitations should be considered when interpreting these findings. First, the sample size was small, which reduces statistical power and the precision of the estimates. Second, the sample was geographically concentrated, with 79.5% of respondents located in Lower Bavaria and Upper Bavaria; perceptions in Franconia, Swabia, and the Upper Palatinate are correspondingly underrepresented, and the findings cannot be generalized to all of Bavaria. Third, the sample was predominantly young and highly educated: half of the respondents were aged 25 to 34 years, and 74.0% held at least a Bachelor's degree. Older adults and respondents with lower formal education, groups whose digital access and attitudes may differ, were underrepresented, which is particularly relevant for a platform intended to be inclusive.

Fourth, all data were self-reported and are therefore subject to social desirability and self-selection bias. Fifth, the cross-sectional design captures perceptions at a single point in time and does not permit causal inference; the regression results describe associations, not effects. Sixth, all item distributions deviated significantly from normality, as is common with Likert-type data, and results based on parametric procedures should be interpreted with corresponding caution. Seventh, the constructs were measured with newly developed items, and their AVE values fell below .50; although composite reliability was adequate, the measurement model should be confirmed with confirmatory factor analysis in a larger, independent sample. Finally, the survey measured perceived feasibility among residents rather than the operational or legal feasibility of implementation itself, and the findings should be read as evidence of respondents' readiness and expectation rather than of institutional capacity.

6. Conclusion

The 10P-Health framework represents a comprehensive, platform-based model of personalized care, extending earlier P-medicine paradigms through ten principles and reflecting the convergence of personalized medicine with digital health, big data, and AI. Realizing such a model in practice depends not only on technical capability but also on public readiness and the perceived feasibility of implementation.

This cross-sectional survey of adult residents of Bavaria found moderate readiness for the 10P-Health platform among respondents. Respondents were broadly experienced with digital health tools, endorsed inclusive access, interoperability, and patient consultation, and expressed conditional trust in AI-supported care under medical supervision. Perceived feasibility was significantly predicted by technological infrastructure, operational readiness, and stakeholder engagement, while legal and regulatory requirements function as a background condition rather than a direct driver of perceived feasibility. The clearest reservations concerned institutional capacity, as system resources and provider preparedness received the lowest ratings in the survey. Within the limits of a regionally concentrated, predominantly young and educated sample, these findings indicate that respondents' attitudes do not present the principal obstacle to a personalized digital health platform in Bavaria, and they identify institutional readiness, transparent data practices, and interoperable infrastructure as the areas in which respondents perceived the greatest need for development. Longitudinal and more representative studies would be required to confirm these associations and to track readiness as implementation proceeds.

Acknowledgements

No acknowledgements were provided.

Conflict of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

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