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RESEARCH ARTICLE

EVALUATING EHEALTH ACCESS AMONG ELDERLY POPULATIONS: A MULTI-METHOD ANALYSIS USING DGRA, TOPSIS, AND KRUSKAL-WALLIS TEST

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ABSTRACT

OBJECTIVE:

The purpose of this study was to identify and rank barriers to obtaining eHealth services among Pakistan's elderly. Older people contributed primary data on technological, individual, relational, environmental, and organizational factors.

DESIGN:

Dynamic Grey Relational Analysis (DGRA) and the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) were utilized on 450 elderly persons to examine and rank the most significant eHealth barriers.

RESULTS:

The most significant barrier was found as "aging limitation (reduction in hearing, sight, memory, and fine motor control)" using both the DGRA and TOPSIS techniques. The Kruskal-Wallis (KW) test was used to assess the significance of this barrier among three age groups of elderly persons. There were no significant differences when the age exceeded 60.

ORIGINALITY:

This study is the first to apply the DGRA, TOPSIS, and KW test to determine the barriers that older people in Pakistan's urban and rural areas face while trying to use eHealth services.

KEYWORDS

eHealth; grey relational analysis; technique for order preference by similarity to ideal solution; kruskal-wallis test; elderly

INTRODUCTION

By 2050, the elderly population in Pakistan (defined as individuals aged 60 years and above) is projected to reach 42.8 million, making up 12.4% of the country's demographic, and showing a growth rate significantly outpacing other age groups [1,2]. As of 2019, rural areas reported that older adults comprised 6.77% of the population, while in urban settings, they accounted for 6.38% [3]. Current estimates by the Bureau of Statistics indicate that individuals aged 60 and above make up 7-8% of the national population, equivalent to 15-17 million people, with approximately 25-30% experiencing disabilities [4]. This translates to 4–5 million elderly facing challenges related to physical, sensory, or cognitive impairments [5]. Moreover, the Supreme Court of Pakistan's 2017 census interventions showed severe loopholes in counting disabled people [6]. The expanding older population, many of whom have health conditions that limit mobility and healthcare access, challenges the healthcare system, especially in undeveloped areas. Given these restrictions there is dire need to highlight the importance of research on elderly populations and barriers to access eHealth services.

The data indicate a clear need for ongoing medical assistance, which is hindered by inadequate healthcare facilities and the underdeveloped eHealth system [7]. eHealth, defined as the utilization of digital and telecommunication technologies in healthcare delivery, presents innovative opportunities for providing age-friendly care to elderly individuals with chronic conditions. In addition to remote management of social and health services through innovative medical delivery methods reduces the necessity for infrequent patient visits, especially in rural areas where health services may be limited [8]. Conversely, it is beneficial in managing conditions such as diabetes, cardiovascular diseases, and hypertension, often termed silent killers, that require constant control [9]. Digital health services can alleviate issues by reducing patient wait times for check-ups and minimizing costs associated with long-distance transportation through tele-help [10]. Despite the numerous advantages of eHealth technology for the elderly, significant barriers persist, complicating its implementation for many individuals in this demographic.

Analysing and discouraging the barriers faced by the elderly in accessing eHealth services is important in addressing the inequalities in health care as well as promoting appropriate healthcare policies. This population is more likely than average to have limited access to normal health care services especially for the elderly who are located in remote geographical regions where the infrastructure is underdeveloped. Understanding these barriers will help to focus the resources where they are highly required, improve the effectiveness of the healthcare sector, and inclusively equip old people with the ability to engage eHealth services. In addition, considerations of eHealth services accessibility can play a huge role in improving the overall life satisfaction levels of elderly patients with chronic illnesses by reducing the need for risky interventions in the case of medical treatment delays and providing constant monitoring as patients' health deteriorates.

Analyzing the challenges faced by the least economically developed countries, such as Pakistan, is essential also due to social issues, the digital divide, and inefficiencies in the healthcare system. A significant portion of the elderly population in society faces challenges in utilizing modern technology, including smartphones and computers, due to limited exposure to these media. This population, residing in rural areas where eHealth is implemented, has limited access to ICT services [7]. Moreover, the disrespect linked to aging or health limitations further isolates elderly patients from the community, diminishing their willingness or capacity to engage with innovations [14]. Furthermore, concerns regarding the protection of individuals' health data online and the utilization of digital health tools contribute to the decision of many individuals to opt out of eHealth services, thereby reinforcing the non-usage of these services and creating an additional barrier [8].

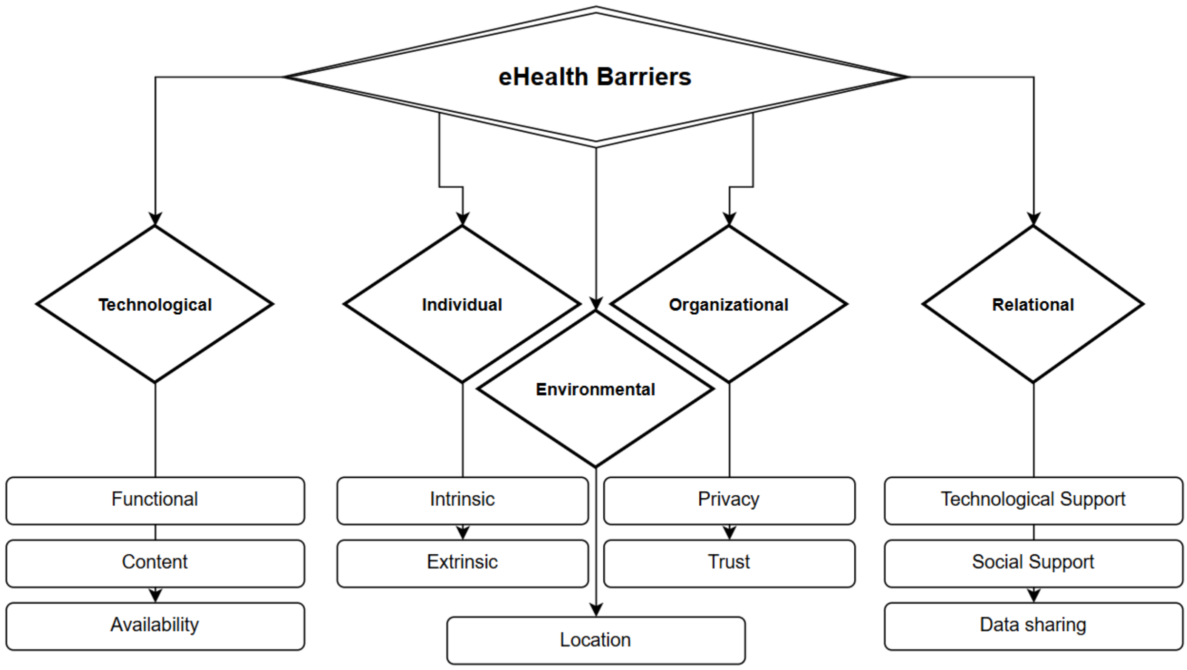
To address these challenges, extensive analysis is essential to identify barriers to eHealth adoption. While numerous studies examine eHealth access barriers among the elderly globally, there remains a distinct gap in understanding these obstacles in the Pakistani context, with age-specific analysis largely unexplored. This study addresses these gaps by employing Dynamic Grey Relational Analysis (DGRA) and the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), well-established multi-criteria decision-making methods [20, 39]—to systematically identify and rank the relative significance of 40 previously validated eHealth barriers. These methods enable objective ranking based on respondent perceptions without requiring assumptions about data distribution, providing policymakers with a clear prioritization of barriers to target. The Kruskal-Wallis (KW) test is subsequently applied to examine whether these barriers vary significantly across age groups within the elderly population. *Table 1* presents the barrier items with criteria and sub-criteria given by [20].

TABLE 1: THE BARRIERS IN ACCESSING EHEALTH SERVICES (SOURCE: AUTHOR'S OWN WORK)

Criteria	Sub-criteria	eHealth Barrier Item
C1: Technological	C1a: Functional	Small screen and text
		Small icons, lack of colour contrast
		Complex functionality
		Poor functionality
	C1b: Content	Lack of alerts
		Alert fatigue: reminders/emails/texts
		Condescending and impersonalized communication, inability to respond to reminders
		Overwhelming and difficult to understand content
		Too much content on one page
	C1c: Availability	Lack of access to electronic equipment
		Cost of electronic equipment and internet service
C2: Individual	C2a: Intrinsic	Ageing limitations: reduction of hearing, sight, memory, and fine motor control
		Perceived self-efficacy
		Lacking confidence in e-health
		Fear and dislike of technology
		No interest in learning
	C2b: Extrinsic	Lack of experience/skills with e-health or technology
		Lack of knowledge of e-health
		Previous negative experience
		Unmet expectations
		Lack of need to change
		Fear that traditional services may perish
		Disbelief in efficacy of e-health
		Lack of external accountability
		Inability to incorporate into routine
		Required effort
		Cultural limitations such as language barriers and e-health detracting from time with family
C3: Relational	C3a: Technological Support	No training/support to learn
		No one to help troubleshoot issues
		Reliance on family for guidance, and lack of family's patience and understanding while learning
	C3b: Social Support	Lack of social interaction
		Absence of interpersonal communication
		Communication through technology considered an 'inauthentic experience'
	C3c: Data sharing	Lack of communication between health platforms
C4: Environmental	C4a: Location	Poor/unreliable internet
C5: Organizational	C5a: Privacy	Health information concerns
	C5b: Trust	Unknown accuracy of information
		Not knowing who people are communicating with
		Concern over management of emergency situations

Figure 1 and *Table 1* present the five validated constructs of eHealth barriers, each representing a category of barriers. The "organizational" identifies 5 barriers, which include the necessity to deliver services or establish infrastructure within the medical sector. The "environmental" construct comprises 1 barrier, which pertain to small yet irrefutable geographical and social environmental challenge, such as geographical distances. The "relational" construct, conversely, comprises 7 barriers that presumably signify a disruption in the communication and interaction processes among elderly users, their caregivers, and medical personnel. The "individual" construct presents the most significant barriers totalling 16, including individuals' abilities, computer literacy, health, and motivation, which contribute to the non-evidence-based utilization of eHealth tools. Finally, the subsequent component is "technological," which encompasses over 11 barriers, indicating concerns related to screen complexity, among others.

FIGURE 1: CRITERIA AND SUB-CRITERIA OF EHEALTH BARRIERS (SOURCE: AUTHOR'S OWN WORK)



METHODOLOGY

This study utilized a cross-sectional research design to investigate the challenges encountered by elderly individuals (aged 60 and above) in accessing eHealth services in Pakistan. This design is well-suited for exploratory studies aiming to identify and rank barriers at a single point in time, particularly when employing multi-criteria decision-making techniques such as DGRA and TOPSIS, which do not require longitudinal data to establish relative rankings. Out of one thousand individuals approached, 450 responded to the survey, with all completing all sections and included in the final analysis. The sample included male and female participants from both urban and rural areas across Pakistan to ensure diverse geographic and socioeconomic representation. The sample was stratified by geographic location, and purposive sampling was employed to capture diverse socioeconomic backgrounds and varying levels of familiarity with digital technologies. The 1,000 potential participants were approached in person at outpatient departments of public hospitals, rural basic health units, elderly day-care centers, and community gathering places (including mosques and senior citizen clubs) across four districts of Punjab and Sindh provinces.

This approach was deliberately chosen for two reasons: first, elderly populations in Pakistan, particularly those in rural areas or with mobility limitations, constitute a hard-to-reach demographic for which comprehensive sampling frames are not publicly accessible; second, the objective was to capture the breadth of perceived barriers across diverse subgroups rather than to produce statistically generalizable prevalence estimates. Similar methodological approaches have been widely adopted in eHealth barrier research among elderly populations in low- and middle-income country contexts [10, 13, 15]. Given Pakistan's linguistic diversity, the survey was designed in both Urdu and relevant local languages to ensure accurate understanding. A structured questionnaire captured demographic information (gender, age, education level, geographic location) and addressed 40 previously validated eHealth barriers [15], adapted to Pakistan's context. Where necessary, questionnaires were read and explained to participants to accommodate visual impairments or limited literacy. To enhance data accuracy, four attention checks were embedded in the survey. This study received ethical approval from the Institutional Review Board of the University of the Punjab, Pakistan (Approval No. PU/IRB/2025-43, dated 15 September 2025), and all procedures were in accordance with institutional ethical standards. All participants provided verbal informed consent after a full explanation of the study objectives and their right to withdraw at any time without consequence.

Table 2 presents the demographic characteristics of the 450 elderly participants included in this study. The sample comprised 58.9% males (n=265) and 41.1% females (n=185), reflecting the relatively greater accessibility of male respondents in the Pakistani cultural context. A key strength of this study is the balanced distribution across age groups, with 34.4% aged 60-69 years (n=154), 34.23% aged 70-79 years (n=150), and 32.2% aged 80 years and above (n=145), allowing for robust comparative analysis across the entire elderly spectrum. Geographic representation was reasonably balanced between urban (53.3%, n=240) and rural (46.7%, n=210) areas, capturing diverse experiences of eHealth accessibility across different settings. Regarding educational attainment, nearly half of the participants (46.7%, n=210) had no formal education or only junior schooling, while 26.7% (n=120) had completed intermediate education. Higher education levels were less common, with 12.2% (n=55) holding bachelor's degrees and only 7.8% (n=35) having master's degrees. This educational profile aligns with the national literacy trends among older adults in Pakistan and has important implications for eHealth service design, particularly regarding digital literacy requirements and user interface accessibility.

TABLE 2: DEMOGRAPHIC PROFILE OF THE STUDY SAMPLE (N=450) (SOURCE: AUTHOR'S OWN WORK)

Variable	Category	Frequency (n)	Percentage (%)
Gender	Male	265	58.90%
	Female	185	41.10%
Age Group	60 - 69 years	154	34.23%
	70 - 79 years	151	33.55%
	80 years and above	145	32.22%
Geographic Location	Urban	240	53.30%
	Rural	210	46.70%
Education Level	No Formal / Junior Schooling	210	46.70%
	Intermediate (High School)	120	26.70%
	Bachelor's Degree	55	12.20%
	Master's Degree	35	7.80%

To clarify the study's logical structure, the research data was organized and summarized. The analysis was divided into three main sections: GRA and TOPSIS, and the KW test, with results and interpretations presented for each. The manuscript structure is as follows: The introduction establishes the relevance of assessing eHealth barriers for elderly individuals in Pakistan, while the next section provides the theoretical foundation and application of Grey Systems Theory (GST) and GRA. The research approach follows, detailing the identification of 40 barriers and the analytical methods, GRA, TOPSIS and KW test, used to evaluate them. Subsequent sections discuss findings from the barrier rankings, supported by graphical representations. The manuscript concludes with an overview of the study's contributions and final remarks.

ANALYTICAL FRAMEWORK

The methodology relied on the application of DGRA and TOPSIS techniques. The choice of methods simplified the controlled evaluation of the barriers that were recognised, including classification of these barriers in terms of their severity and usefulness towards promoting effective eHealth services. Through application of both DGRA and TOPSIS approaches, it provided a more detailed analysis of the key factors that serve to impede the elderly in effective adoption of eHealth facilities, which accounts for contextual relevance in different age cohorts. Descriptive statistics also facilitated the description and organization of the data used in the analysis, which is the demographic attribute of the sample. Particularly, the data were analysed through the groups of age difference in order to observe the variation of barriers to eHealth adoption. This approach also allowed providing a clear picture of the challenges experienced by elderly individuals in Pakistan and plans for interventions were formulated.

RESEARCH INSTRUMENT

The identification of barriers to using eHealth services was carried out in accordance with [20] and the opinions of experts. They found five different constructs, each of which contained various factors and forty different barriers. These barriers were originally identified by Wilson et al. [20] through a comprehensive scoping review of 3536 papers published in Scopus, Medline, Psychology and Behavioral Sciences, Embase, PsycINFO, and CINAHL, establishing a validated framework of eHealth barriers for elderly individuals all over the world. This framework was subsequently adapted and validated for the Pakistani context through expert opinions and pilot testing, following the approach employed in previous eHealth research [10, 11, 12, 13]. In order to assess the extent to which users perceive the negative implications of those barriers, the respondents were provided an instrument including five-points Likert scale that included strongly disagree, disagree, neutral, agree and strongly agree. The questionnaire tool was divided into 2 parts. In the first section, the respondents provided their demographics information whereas in the second section, they provided the data on 40 barriers they are facing in accessing eHealth services.

DATA ANALYSIS

DYNAMIC GREY RELATIONAL ANALYSIS

Deng's GRA is a prominent method within Grey System Research Analysis (GSRA) [16]. A critical parameter of Deng's GRA is the distinguishing coefficient (ξ), which scholars typically assign a value of 0.5. However, some studies have contested this convention, as demonstrated by Xie and Liu [17], while others have verified these objections [18]. Subsequently, Angela and Angelina [19] introduced a generalized version of this model, termed the Dynamic Grey Relational Analysis (DGRA), which has been well received by contemporary scholars [20]. Following this, Delcea and Cotfas [21] and Ouali [22] validated the DGRA's validity. The DGRA is predicated on the dynamic Grey Relational Grade (GRG; $\mathit{\Gamma}_{0k}$). Let us assume that n respondents rated m barriers (or factors) using 5-point Likert scale. Then, the GRG will be given by Angela and Angelina [19],

$$\mathit{\Gamma}_{0k} = \frac{1}{n}\sum_{j=1}^{n}\gamma_{0k}(j) \tag{1}$$

where, the dynamic Grey Relational Coefficient (GRC; $\gamma_{0k}(j)$) is,

$$\gamma_{0k}(j) = \frac{\mathit{\Delta}_{min}+\xi(j)\mathit{\Delta}_{max}}{|\mathit{\Delta}_{0k}(j)|+\xi(j)\mathit{\Delta}_{max}}, k = 1,2, \dots . m \tag{2}$$

Here,

$$|\mathit{\Delta}_{0k}(j)| = |x_0(j) - x_k(j)| \tag{3}$$

$$\mathit{\Delta}_{min} = min_k min_j |x_0(j) - x_k(j) \tag{4}$$

$$\mathit{\Delta}_{max} = max_k max_j |x_0(j) - x_k(j)| \tag{5}$$

$$\xi(j) = \{\xi(1), \xi(2), \dots, \xi(n)\}, \xi(j) \in (0, 1] \tag{6}$$

The procedure to obtained $\xi(j)$ is reported in [19]. In this study, a dynamic GRA model was built and executed using Microsoft Excel. Because the sample size was small, it is important to report the Grey Relational Standard Deviation (GRSD); therefore, uncertainty analysis can also be performed, and one can see the range in which the GRG values can vary. The GRSD between the ideal data set $X_0$and comparative data sets $X_k$is calculated as per Angela and Angelina [19],

$$\sigma_{\Gamma_{0k}} = \sqrt{\frac{\sum_{j=1}^{n}\left(\Gamma_{0k}-\gamma_{0k}(j)\right)^2}{n-1}} \quad (7)$$

Subsequently, by multiplying the ranks associated with GRG and GRSD, one can obtain the Rank Product Score (RPS), which is a convenient way to cluster the barriers.

Table 3 presents the Grey Relational Grades (GRG) and corresponding rankings for all 40 eHealth barriers evaluated in this study. The results reveal that barriers within the individual construct dominate the highest rankings, with aging limitations (C2a.I1), perceived self-efficacy (C2a.I2), and lacking confidence in e-health (C2a.I3) occupying the top three positions. Other individual barriers, including fear and dislike of technology (C2a.I4), no interest in learning (C2a.I5), lack of experience (C2b.E1), and lack of knowledge (C2b.E2), also feature prominently within the top ten, underscoring the critical role of personal factors in eHealth access. Privacy concerns (C5a.P1) and alert fatigue (C1b.C2) represent the highest-ranked organizational and technological barriers, respectively, indicating that systemic and design-related issues also warrant attention. Conversely, environmental barriers such as poor internet connectivity (C4a.L1) and relational barriers including lack of social interaction (C3b.S1) and absence of interpersonal communication (C3b.S2) occupy the lowest ranks, suggesting these are perceived as less impedimental. The upper and lower bound values (GRG-U and GRG-L) demonstrate the range of uncertainty in the GRG estimates, with narrower bounds indicating greater consensus among respondents. The Rank Product Score (RPS) further refines the ordering by combining GRG and GRSD ranks, with lower RPS values indicating more consistently rated barriers, as seen for C5b.T4 (RPS=17) and C1b.C5 (RPS=33).

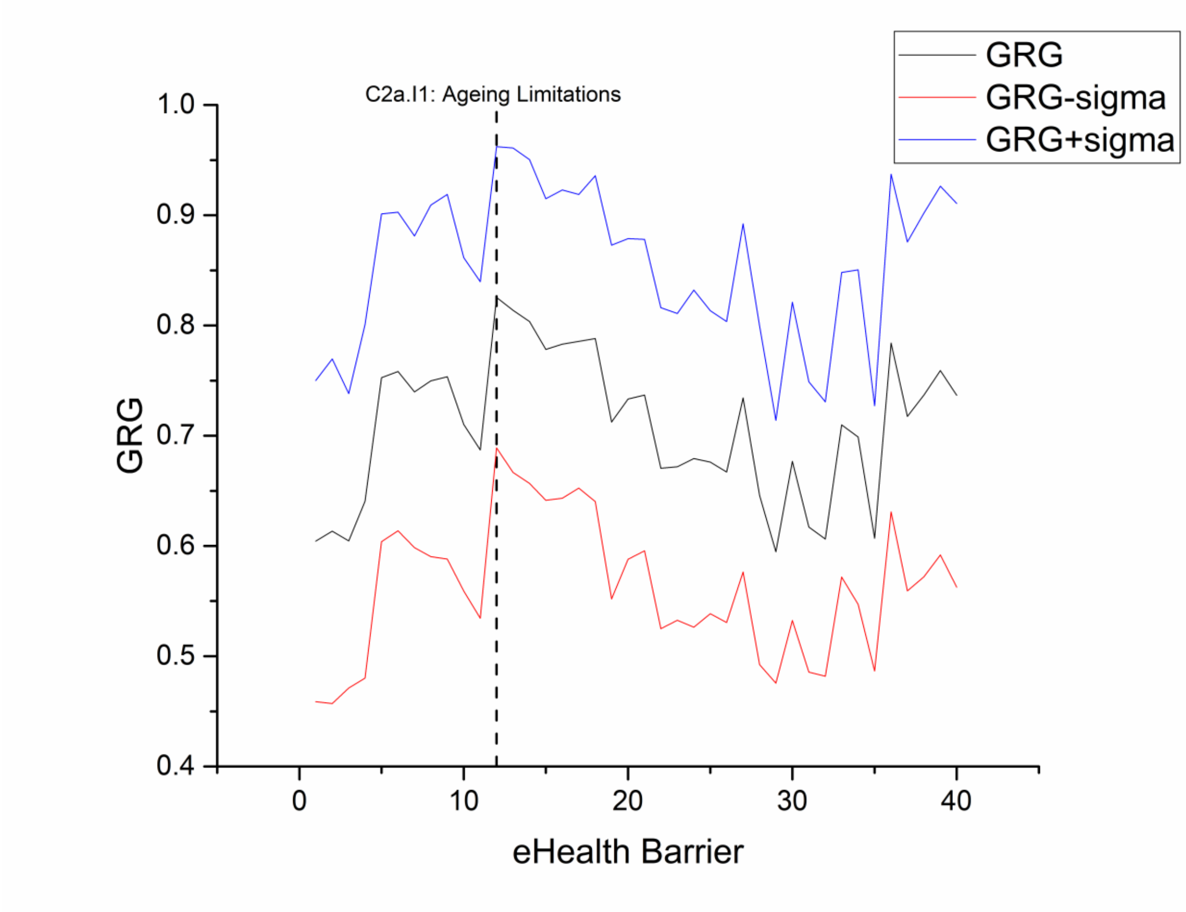
TABLE 3: GREY RELATIONAL EVALUATION OF EHEALTH BARRIERS (SOURCE: AUTHOR'S OWN WORK)

Code of Barriers	GRG	Rank (GRG)	GRSD	Rank (GRSD)	GRG (L)	GRG (U)	RPS
C1a.F1	0.604342	39	0.145674	21	0.458668	0.750015	819
C1a.F2	0.613371	35	0.156261	10	0.457109	0.769632	350
C1a.F3	0.604626	38	0.133535	35	0.471091	0.738161	1330
C1a.F4	0.640499	33	0.160393	6	0.480106	0.800891	198
C1b.C1	0.752558	12	0.148712	17	0.603846	0.90127	204
C1b.C2	0.758203	10	0.144534	24	0.613669	0.902737	240
C1b.C3	0.739796	14	0.141385	26	0.598411	0.88118	364
C1b.C4	0.749747	13	0.159401	7	0.590346	0.909147	91
C1b.C5	0.753481	11	0.165365	3	0.588116	0.918846	33
C1c.A1	0.71023	22	0.151173	16	0.559056	0.861403	352
C1c.A2	0.687091	25	0.152582	14	0.53451	0.839673	350
C2a.I1	0.825486	1	0.136569	33	0.688917	0.962056	33
C2a.I2	0.813795	2	0.147075	19	0.66672	0.96087	38
C2a.I3	0.803502	3	0.146854	20	0.656648	0.950356	60
C2a.I4	0.778219	8	0.136758	32	0.641461	0.914976	256
C2a.I5	0.783106	7	0.139773	28	0.643333	0.922879	196
C2b.E1	0.785652	5	0.133124	36	0.652529	0.918776	180
C2b.E2	0.788048	4	0.147769	18	0.64028	0.935817	72
C2b.E3	0.712397	21	0.160483	5	0.551914	0.87288	105
C2b.E4	0.733347	19	0.145424	23	0.587923	0.878771	437
C2b.E5	0.736853	16	0.141284	27	0.595568	0.878137	432
C2b.E6	0.670533	30	0.145612	22	0.524921	0.816145	660
C2b.E7	0.671752	29	0.139087	29	0.532665	0.81084	841
C2b.E8	0.679205	26	0.152835	13	0.52637	0.83204	338
C2b.E9	0.675984	28	0.137469	31	0.538515	0.813453	868
C2b.E10	0.667127	31	0.136514	34	0.530613	0.803641	1054

C2b.E11	0.734341	18	0.157915	9	0.576426	0.892256	162
C3a.T1	0.64592	32	0.153568	11	0.492352	0.799488	352
C3a.T2	0.594786	40	0.119192	40	0.475594	0.713978	1600
C3a.T3	0.676742	27	0.144381	25	0.532361	0.821123	675
C3b.S1	0.617178	34	0.131672	37	0.485506	0.74885	1258
C3b.S2	0.606308	37	0.124485	38	0.481823	0.730792	1406
C3b.S3	0.709922	23	0.138081	30	0.57184	0.848003	690
C3c.D1	0.698768	24	0.15167	15	0.547099	0.850438	360
C4a.L1	0.606881	36	0.120259	39	0.486622	0.72714	1404
C5a.P1	0.784028	6	0.153123	12	0.630905	0.937152	72
C5b.T1	0.717429	20	0.15823	8	0.5592	0.875659	160
C5b.T2	0.73688	15	0.164952	4	0.571928	0.901832	60
C5b.T3	0.759081	9	0.167295	2	0.591786	0.926375	18
C5b.T4	0.736731	17	0.174035	1	0.562696	0.910766	17

Figure 2 presents the Dynamic Grey Relational Grades (GRG) with upper (GRG + sigma) and lower bounds (GRG - sigma) for key eHealth barriers, where higher GRG values indicate greater significance. Individual construct barriers, particularly aging limitations (C2-a1/2, GRG=0.82) and perceived self-efficacy (C2-a1/4, GRG=0.80), demonstrate the highest values with relatively narrow confidence intervals, reflecting strong respondent consensus on their primary importance. Technological barriers such as alert fatigue (C1b-C5, GRG=0.74) and condescending communication (C1b-C3, GRG=0.75) occupy mid-range positions with wider bounds, indicating greater perceptual variability. Environmental (C4-a1, GRG=0.62) and functional barriers (C1a-F1, GRG=0.60) rank lowest, suggesting they are perceived as less critical obstacles to eHealth access among elderly individuals.

FIGURE 2: DGRA BASED RANKING OF EHEALTH BARRIERS (SOURCE: AUTHOR'S OWN WORK)



TECHNIQUE FOR ORDER PREFERENCE BY SIMILARITY TO IDEAL SOLUTION

TOPSIS is a domain of operations research dedicated to creating computational and mathematical tools to aid decision-makers in evaluating performance criteria subjectively. Numerous challenges in decision-making in the actual world can be addressed. Ranking of alternatives based on TOPSIS, developed by Hwang and Yoon [39], aimed at identifying an object with the maximum score, referred to as the positive ideal solution (PIS), and the minimum score, termed the negative ideal solution (NIS). Recently, numerous methodologies have been introduced for addressing DGRA and TOPSIS methods; for instance, Matambo [23] evaluate e-commerce barriers through DGRA, and Yoon and Hwang [24] applied TOPSIS. Li et al. [25] developed Grey Multiple Attribute Decision Making (GMADM), while Ma [26] and, Yang and Hu [27] explored novel approaches utilizing fuzzy β covering techniques. Additionally, Atef and Liu [28] proposed Multiple Attribute Grey Decision Making (MAGDM) inspired by the concepts of Yoon and Hwang [24], among others Mardani et al. [29] , Sun et al. [30] , Zhang et al. [31] , and Derici and Dogan [32].. Therefore, the subsequent procedure is executed:

STEP 1. The normalized matrix was calculated as:

$$N(x_{ij}) = \frac{x_{ij}}{\sqrt{\sum_{j=1}^{n} x_{ij}^2}} \qquad (8)$$

STEP 2. Calculate the weighted normalized matrix.

$$K_{ij} = N(x_{ij}) * W_j, \qquad (9)$$

where W is the weight vector such that $\sum_{j=1}^{n} W_j = 1$.

STEP 3. Calculate the ideal best $K_j^+ = \max(K_{ij})$ and worst $K_j^- = \min(K_{ij})$ value.

STEP 4. The distance from the ideal best was calculated using the following formula:

$$D_i^+ = \sqrt{\sum_{j=1}^{n} (K_{ij} - K_j^+)^2} \qquad (10)$$

STEP 5. Hence, the distance for the ideal worst case was computed as follows:

$$D_i^- = \sqrt{\sum_{j=1}^{n} (K_{ij} - K_j^-)^2} \qquad (11)$$

STEP 6. Calculate the score, and then rank the alternatives.

$$S_i = \frac{D_i^-}{D_i^+ + D_i^-} \qquad (12)$$

Table 4 presents the TOPSIS rankings of eHealth barriers, showing remarkable consistency with the DGRA findings. Individual construct barriers dominate the top positions, with aging limitations (C2a.I1), perceived self-efficacy (C2a.I2), and lacking confidence in e-health (C2a.I3) ranked first, second, and third, respectively. Lack of experience (C2b.E1) and no interest in learning (C2a.I5) complete the top five, underscoring the primacy of personal factors in hindering eHealth access. Privacy concerns (C5a.P1) emerged as the highest-ranked organizational barrier at eighth position, while alert fatigue (C1b.C2) and lack of alerts (C1b.C1) were the top technological barriers at ninth and tenth, respectively. At the lower end, functional barriers (C1a.F1-F3), lack of social interaction (C3b.S1), and absence of interpersonal communication (C3b.S2) ranked among the lowest, suggesting these are perceived as less critical.

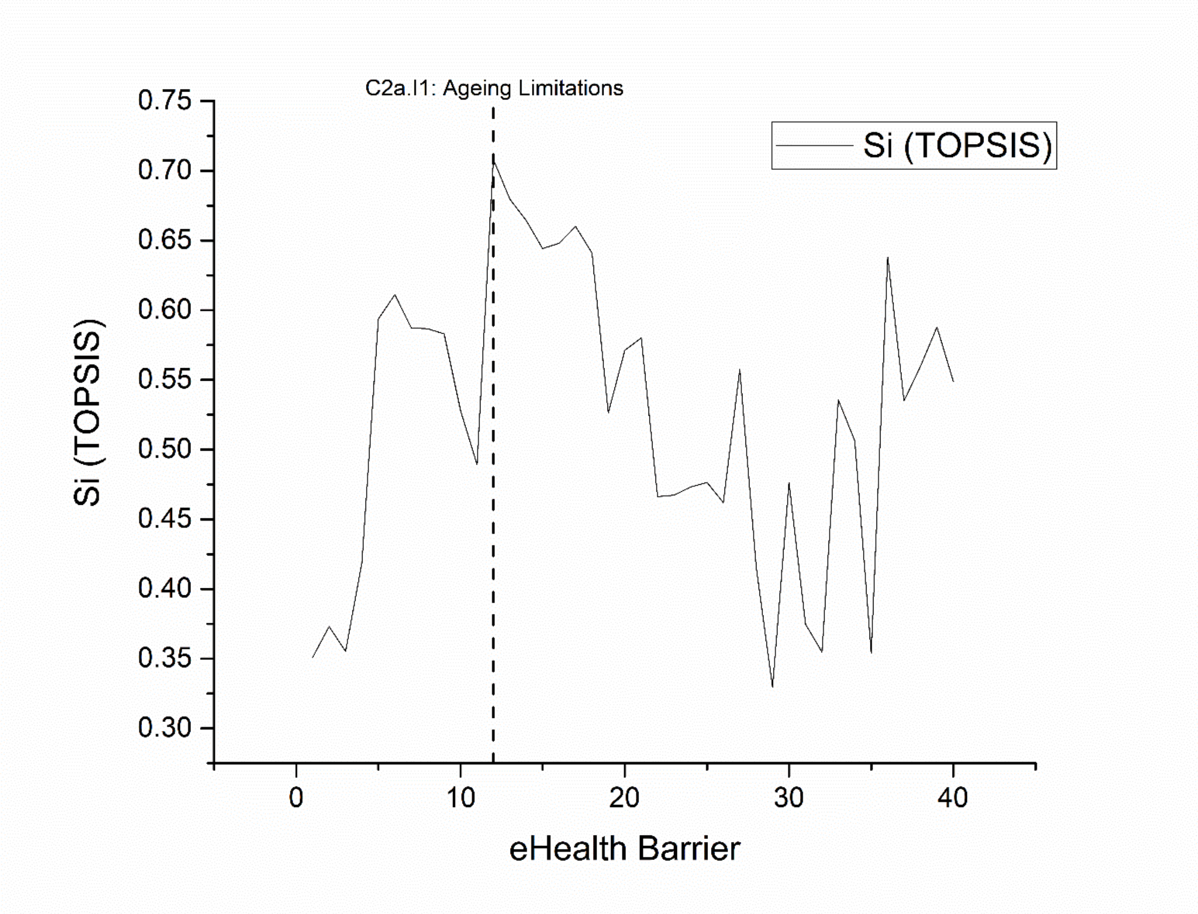
TABLE 4: ORDERING ALTERNATIVES THROUGH TOPSIS (SOURCE: AUTHOR'S OWN WORK)

Coding of Barriers	D_i^+	D_i^-	S_i	Rank
C1a.F1	0.662163	0.357984	0.350914	39
C1a.F2	0.660505	0.393024	0.373055	35
C1a.F3	0.649519	0.357792	0.355195	36
C1a.F4	0.611476	0.440544	0.41876	32
C1b.C1	0.394417	0.576281	0.593677	10
C1b.C2	0.371512	0.583842	0.611127	9
C1b.C3	0.391277	0.556683	0.587243	12
C1b.C4	0.40403	0.57342	0.586649	13

C1b.C5	0.409254	0.572343	0.583073	14
C1c.A1	0.463143	0.517908	0.527912	22
C1c.A2	0.503959	0.482847	0.489303	25
C2a.I1	0.27331	0.663197	0.70816	1
C2a.I2	0.305962	0.649202	0.679676	2
C2a.I3	0.322961	0.638774	0.664189	3
C2a.I4	0.334018	0.604941	0.644268	6
C2a.I5	0.332579	0.612261	0.648005	5
C2b.E1	0.315229	0.612037	0.660044	4
C2b.E2	0.3469	0.619272	0.640954	7
C2b.E3	0.462402	0.514057	0.52645	23
C2b.E4	0.406735	0.541962	0.57127	16
C2b.E5	0.397532	0.549247	0.580122	15
C2b.E6	0.518305	0.452818	0.466283	30
C2b.E7	0.521337	0.457485	0.467383	29
C2b.E8	0.521469	0.468293	0.473137	28
C2b.E9	0.505453	0.460025	0.476474	26
C2b.E10	0.525136	0.450998	0.462025	31
C2b.E11	0.437108	0.550369	0.557348	18
C3a.T1	0.586185	0.416721	0.415514	33
C3a.T2	0.655296	0.322111	0.329557	40
C3a.T3	0.507482	0.461066	0.476038	27
C3b.S1	0.617832	0.370403	0.374813	34
C3b.S2	0.634144	0.348477	0.354641	37
C3b.S3	0.441321	0.509369	0.535789	20
C3c.D1	0.481141	0.493516	0.506348	24
C4a.L1	0.624671	0.342327	0.35401	38
C5a.P1	0.350047	0.617499	0.638211	8
C5b.T1	0.462847	0.532265	0.53488	21
C5b.T2	0.439765	0.559385	0.55986	17
C5b.T3	0.413088	0.589217	0.587862	11
C5b.T4	0.462106	0.562683	0.549072	19

Figure 3 illustrates the TOPSIS performance scores for selected eHealth barriers, where higher values indicate greater significance. Consistent with the DGRA findings, individual construct barriers dominate the upper range, with aging limitations (C2-a12, score=0.71) and perceived self-efficacy (C2-a14, score=0.67) achieving the highest scores, followed closely by lack of experience (C2-b1-E1, score=0.66). Technological content barriers, including condescending communication (C1b-C3, score=0.60) and alert fatigue (C1b-C5, score=0.59), occupy the mid-range, indicating moderate importance. Notably, environmental factors (C4-a1, score=0.64) show relatively higher scores in this visualization, suggesting some regional variation in perceived barriers. Functional barriers (C1a-F1, score=0.35; C1a-F3, score=0.37) and relational barriers (C3-b1, score=0.32; C3-b3, score=0.36) cluster at the lower end, reinforcing that technical complexities and social support concerns, while relevant, are secondary to individual capacity and health-related limitations in explaining eHealth access challenges among elderly populations.

FIGURE 3: TOPSIS BASED RANKING OF EHEALTH BARRIERS (SOURCE: AUTHOR'S OWN WORK)



KRUSKAL-WALLIS TEST

The KW test is a nonparametric alternative to ANOVA Wissing and Timm [33] and can be viewed as a generalized form of the Mann-Whitney test Du Prel et al. [34]. This test evaluates whether distributions differ across three or more independent groups by comparing their mean ranks. In this study, the KW test was applied to examine differences across three age groups of elderly participants, 60-69 years (n = 155), 70-79 years (n = 150), and 80+ years (n = 145), using IBM® SPSS® 24 software for statistical analysis. The null hypothesis tested was that the mean ranks across these groups are equivalent. Elderly individuals over the age of 60 face comparable challenges in performing daily activities, primarily due to physical and cognitive limitations associated with aging. Differences between the age groups, 60-69, 70-79, and 80+, were expected to be minimal. To explore this, we applied the KW test to assess any significant differences across these age groups within the elderly population. Below given are the steps to apply KW test:

STEP 1: Rank all of the scores, regardless of which group they belong to; the lowest score receives the lowest ranking.

STEP 2: Calculate T_g, the sum of the ranks in each group. Simply add up all of the ranks for each category in turn.

STEP 3: Find H as

$$H = \left[\frac{12}{N(N+1)} * \sum \frac{{T_g}^2}{n_g}\right] - 3 * (N+1) \qquad (13)$$

Where N is the total number of respondents, T_g is the rank sum of each demographic group, and n_g is the number of respondents in each group. The current study employed IBM SPSS software to administer this test to four groups (age, gender, education, marital status, and participant category).

STEP 4: The degrees of freedom (df) equal the number of groups minus one. We have four groups with three degrees of freedom.

STEP 5: The number of groups and participants determines how significant H is.

In accordance with the assumptions of the KW test and the focus of our study, we formulated the following null (H_0) and alternative (H_1) hypotheses.

H_0: There is no significant difference in barrier to access eHealth services across different age groups of the elderly.
H_1: There is a significant difference in barrier to access eHealth services across different age groups of the elderly.

Evaluation of eHealth service barriers across the three age groups using the KW test revealed no significant differences, as indicated by an asymptotic significance level of 0.487 ($p > 0.05$) (see *Table 5*). This result supports the acceptance of the null hypothesis, confirming that barriers to eHealth access are comparable across the age groups studied, and there is no significant difference found among age groups.

TABLE 5: KRUSKAL-WALLIS TEST RESULTS FOR BARRIERS ACROSS AGE GROUPS (SOURCE: AUTHOR'S OWN WORK)

Mean Barriers	Age Group	Sample (n)	Mean Rank
	60-69 years	154	226.34
	70-79 years	151	231.78
	80 years and above	145	218.62
Chi-Square	1.452		
Degree of Freedom	2		
Asymp. Sig.	0.487		

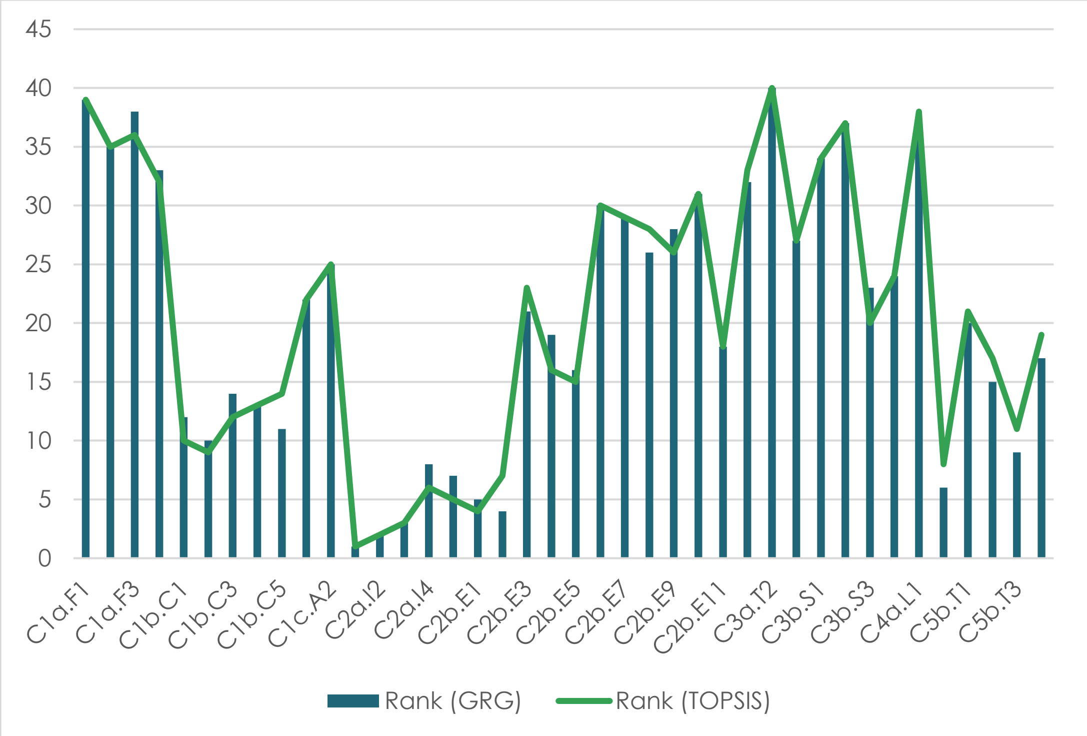
DISCUSSION

The findings from this study provide critical insights into the barriers affecting eHealth access among elderly individuals in Pakistan, with important implications for healthcare policy and digital health infrastructure development. The application of both DGRA and TOPSIS methods consistently identified "aging limitations" including reductions in hearing, sight, memory, and fine motor control, as the most significant barrier across all analyses, underscoring the fundamental role of age-related physiological changes in shaping digital health engagement. Notably, most of the top ten barriers belonged to the "individual" construct, suggesting that personal factors such as perceived self-efficacy, lack of confidence in eHealth, and fear of technology, collectively represent the most formidable obstacles to eHealth adoption among older adults. The organizational construct emerged as the second most impactful category, highlighting systemic issues related to privacy concerns, trust in digital platforms, and emergency management that require coordinated responses from healthcare institutions.

Importantly, the KW test results ($\chi^2 = 1.452$, $p = 0.487$) confirmed that these barriers are experienced uniformly across all age groups (60-69, 70-79, and 80+ years), suggesting that interventions should adopt a universal design approach rather than targeting specific age cohorts. The balanced sample distribution achieved in this study (n=450 with 145-155 respondents per age group) strengthens the validity of these findings and addresses methodological concerns regarding underrepresentation of the oldest-old population. From a policy perspective, these results underscore the urgent need for age-sensitive eHealth solutions that accommodate age-related impairments through features such as voice-activated interfaces, adjustable text sizes, simplified navigation, and AI-driven assistance, while simultaneously addressing organizational barriers through transparent data governance and digital literacy programs tailored to Pakistan's diverse elderly population.

A comparison of the rankings obtained from DGRA and TOPSIS reveals notable consistency in the identification of critical barriers to eHealth access among elderly individuals, presented in *Figure 4*. Barriers within the individual construct, particularly those related to intrinsic aging limitations (C2.a1.1) and extrinsic factors such as lack of experience (C2.b1.E1), consistently ranked among the highest in both methods, reinforcing their prominence as primary obstacles. Technological barriers related to content complexity (C1b.C3) and alert fatigue (C1b.C5) also showed strong alignment across both ranking techniques. Conversely, environmental (C4a.L1) and relational barriers (C3b.S1, C3b.S3) were consistently ranked lower by both methods, suggesting they are perceived as less impedimental. This convergence between DGRA and TOPSIS rankings enhances the reliability of the findings and provides robust evidence base for prioritizing interventions targeting the most impactful barriers.

FIGURE 4: COMPARATIVE ANALYSIS OF EHEALTH BARRIERS (SOURCE: AUTHOR'S OWN WORK)



CONTRIBUTION OF THE STUDY

This study adds to the body of knowledge of GST in the following ways. First, this is the first study to use DGRA, TOPSIS, and KW test focusing on the elderly population of Pakistan. Previous research has shown that policies need to be specific to the needs of older adults in the perspective of telehealth services. Second, we used a Likert scale to collect data to learn more about elderly individuals' perceptions, which provides richer insights compared to other studies. Third, the study highlights the importance of considering different age groups among the elderly, which provides valuable insight to healthcare policy makers to formulate strategies. This helps them set goals and address eHealth barriers effectively. It is important to pay attention to both the top barrier and the top set of barriers. eHealth segments such as eHealth apps, online doctor consultations, online pharmacies, and eHealth gadgets are associated with the evaluated eHealth barriers. Considering the growing rate of the elderly population in Pakistan, healthcare policy makers need to offer a wide range of services in home, community, and institutional settings that are well-balanced and specifically designed to meet the wants and needs of older adults.

The findings highlight the importance of continuing to work on projects and actions that make eHealth primary care services easier to access, as also suggested by Bardhan and Ashraf [35]. For the elderly in Pakistan, building long-term eHealth primary care infrastructure is very important because it is linked to the work of hospitals and the government. Studies have shown the effectiveness of comprehensive long-term care systems in other regions, highlighting the possible benefits of similar approaches in Pakistan [8]. Furthermore, research indicates that when elderly individuals perceive ICT as useful and relevant to their daily tasks, they are increasingly likely to adopt and engage with these technologies.

IMPLICATIONS AND RECOMMENDATIONS

The findings carry significant implications for healthcare policy and practice in Pakistan. The consistent ranking of "aging limitations" (reductions in hearing, sight, memory, and fine motor control) as the most critical barrier underscores the need for age-sensitive eHealth design, including voice-activated interfaces, adjustable text sizes, and simplified navigation.

Healthcare policymakers should mandate accessibility standards for digital health platforms and integrate digital literacy programs into primary healthcare services, leveraging community health workers to provide hands-on training for elderly individuals in both urban and rural settings. The prominence of privacy and trust-related barriers further indicates that healthcare institutions must develop transparent data governance policies tailored to elderly users. For practitioners, eHealth interventions should be introduced gradually, beginning with simple task-specific applications such as medication reminders, to build self-efficacy and reduce technology-related anxiety. Finally, as the KW test confirmed no significant differences across age groups (p = 0.487), a universal design approach rather than age-segmented interventions represents the most efficient and equitable strategy for improving eHealth access among Pakistan's elderly population.

CONCLUSION

This research utilized a mixed-method approach that incorporated both DGRA and TOPSIS, in addition to the KW test. DGRA and TOPSIS techniques were employed to identify and rank the barriers encountered by elderly individuals in accessing eHealth services. The KW test was employed to examine the significant difference in top ranked barrier to access eHealth services among various age groups of the elderly. Together, these methods provide a robust foundation for targeted policy interventions and the development of age-sensitive eHealth strategies aimed at reducing healthcare disparities among older adults in Pakistan.

Using the constructs of technology, individual, relational, environmental, and organizational factors, the DGRA and TOPSIS analyses identified the 'Individual' construct as the most impactful barrier to eHealth access among elderly individuals. The primary barrier, 'aging limitations', including reductions in hearing, sight, memory, and fine motor skills, was consistently recognized as the most significant obstacle across analyses. The KW test further confirmed that this barrier affects all elderly age groups similarly, with no statistically significant differences observed between age groups over 60. This finding suggests that policymakers should prioritize addressing aging-related limitations uniformly across the elderly population in eHealth policy planning. To mitigate these barriers effectively, enhancements in the eHealth sector should incorporate user-friendly technologies, such as thumbprint authentication, AI-driven assistance, and eye-tracking features, designed to accommodate age-related impairments and improve accessibility for all elderly users.

This study has limitations, notably the reliance on cross-sectional data, which restricts the ability to establish causal relationships. Subsequent investigations employing longitudinal data may broaden the applicability of this study. Second, our study encompasses elderly individuals who indicated insufficient access to ICT. The implementation of eHealth services is dependent on the accessibility of the eHealth segment, which constrains their utilization. The implementation of internet of things (IoT) systems and digital health technologies has the potential to improve healthcare accessibility and autonomy for the elderly. Third, the study did not address the aspirations of older adults; therefore, eHealth service providers should foster an interest in technology among this demographic. The findings suggest that individuals with a natural curiosity and interest in technology are more likely to adopt eHealth services and engage with various eHealth primary care platforms. Four, the current study did not consider the potential impact of additional factors that may act as facilitators, including individuals' ambitions and tendencies to embrace a new lifestyle, as well as their aspirations to contribute to scientific progress by participating in eHealth program research trials. Future studies should concentrate on the facilitating factors. International health organizations, including the WHO, underscore the necessity of incorporating digital health into healthcare policies to enhance health systems. Five, GRA, TOPSIS, and KW test are the non-parametric statistical techniques applied in this study. To enhance the generalizability of the findings in future studies, non-parametric methods can also be integrated with parametric techniques such as regression analysis and structural equation modelling, as demonstrated in prior studies Khan et al. [36], Jiang et al. [37], and Nawaz et al. [38]. Six, the study employed purposive sampling rather than a probability-based sampling framework derived from official census data (e.g., Pakistan Bureau of Statistics). While this approach was appropriate for capturing diverse perspectives across hard-to-reach elderly subgroups and for the exploratory ranking objectives of this study, the findings may not be statistically representative of Pakistan's entire elderly population. Future research should consider probability sampling methods where feasible to enhance generalizability.

Seven, considering the advancement of methodology, future studies may also incorporate additional multi-criteria decision-making methods, such as the Analytical Ordinal Priority Approach (AOPA), to further validate and extend the ranking results presented here. Finally, the questionnaire tool lacked identification checks concerning health or functional limitations. The study was thus constrained in assessing the ranking of barriers according to the level of physical or cognitive impairment. In light of this research gap, subsequent studies may assess the ranking of barriers according to the severity of age-related limitations through MCDM methodologies and further explore significant differences among impairment levels by utilizing the KW test.

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CONFLICT OF INTEREST

Authors declared no conflict of interest.

DATA AVAILABILITY

The data underlying this article will be shared on reasonable request to the corresponding author.

DECLARATION OF COMPETING INTEREST

Authors have no conflicts of interest to disclose.

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