

When Averages Mislead: Empirically Testing Compensatory vs. Non-Compensatory Patient Evaluation Logic across Healthcare Touchpoints

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Research Article

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Abstract

Background

Patient assessments of healthcare services may not always rely on a compensatory approach where strengths in one area make up for weaknesses in another. This study tests both compensatory and non-compensatory evaluation logic across healthcare touchpoints using survey data from a Saudi healthcare organization.

Methods

The study used a national sample and an independent single-site validation sample. The research combines Partial Least Squares Structural Equation Modeling, Importance-Performance Map Analysis, Necessary Condition Analysis, and a fuzzy aggregation model based on NCA. The fuzzy model used a strict MIN operator, with external validation using the single-site sample without re-estimation.

Results

According to PLS-SEM, there is a strong positive effect of Patient Experience on Overall Patient Satisfaction ($\beta = 0.956$, $p < 0.001$), and IPMA finds Operational and Administrative Process Experience to be a high-importance and low-performance area. NCA showed that eight service sub-dimensions acted as necessary conditions for achieving high patient satisfaction, with Accessibility and Convenience showing the strongest necessity effect ($d = 0.210$). The fuzzy model resulted in an average joint satisfaction-support membership equal to 0.896 (Soft-MIN: 0.906).

Conclusions

Overall, this indicates that although the relationship between experience and satisfaction is strong under the compensatory framework, some conditions may be critical and create barriers. Therefore, the compensatory and non-compensatory approaches should be applied to analyze healthcare services.

1. Introduction

Patient experience is a crucial indicator of healthcare quality and the effectiveness of organizations in modern healthcare systems (Simpson et al., 2022). Due to the increasing emphasis on patient-centered healthcare, it has become imperative to consider patient perceptions about healthcare services rather than focusing only on conventional clinical outcomes (Edgman-Levitan & Schoenbaum, 2021; Wong et al., 2020). Consequently, organizations engaged in healthcare provision consistently gather patient experience data in order to assess the quality of their services, track performance, and support quality improvement efforts. Patient experience depends on several interactions that happen during the process of patients' engagement in healthcare services, often known as healthcare touchpoints. (AlShammari et al., 2025). These touchpoints include enrollment processes, waiting areas, doctor consultations, diagnostic services, pharmacy, and discharge process (Ozcelik et al., 2021). Every interaction adds to patients' views on service quality and affects their general assessment of the healthcare experience. As healthcare delivery is becoming more complex, understanding how the patient integrates experiences from various touchpoints has become an important area of health care research (Javanmardi et al., 2024).

The current system of evaluating healthcare experiences usually relies on compensatory logic, where positive experiences at certain care points can balance out negative ones (Adams et al., 2025; Edgman-Levitan & Schoenbaum, 2021). However, patients may also use a non-compensatory approach, in which extremely bad experiences at particular touchpoints have a more significant influence on their general impression (Adams et al., 2025). This difference leads to questions about whether traditional methods properly reflect how patients form their views on healthcare services in general.

This matter is especially significant as healthcare services involve uncertainty, emotional engagement, and the vulnerability of patients (Javanmardi et al., 2024). In these circumstances, patients might place more importance on adverse experiences that happen during particular phases of treatment. Should patients depend on non-compulsory evaluation methods, existing measurement systems focused mainly on average satisfaction ratings might not effectively reflect true patient perceptions. Healthcare organizations might thus neglect significant flaws even when they obtain acceptable overall ratings (Ghabban, 2025). This raises concerns regarding whether the traditional approach of evaluating patient experience correctly reflects how patients make judgments and emphasizes the necessity to explore how patients develop their overall assessments of healthcare service.

The current research is concerned with the manner in which patients develop general opinions of healthcare services in the course of the treatment process, with particular emphasis on two evaluation procedures: compensatory and non-compensatory (Adams et al., 2025; Oben, 2020). It investigates whether overall opinion of patients is determined by the average of experiences at different points of interaction or by the effect of poor experiences at some moments. Based on these ideas, the study proposes, within the PLS-SEM Compensatory Model, that patient experience positively affects Overall Patient Satisfaction. Secondly, in the research proposition of the Necessary Condition Analysis Model, the study proposes that both main and smaller service aspects are essential for achieving high levels of patient experience and satisfaction (PN1–PN4, PN1a–PN4c). Lastly, for the Fuzzy Non-Compensatory model, the study proposes that the retained necessary sub-dimensions can constrain overall satisfaction through a weakest-link relationship.

The paper is further divided into four parts. In Section 2, the literature review is presented, in which the available literature is reviewed, and areas requiring further research are identified. In Section 3, the methodology employed in conducting the research is presented. This entails the sources and methods used in collecting and analyzing the data. The findings of this research are presented and discussed in Section 4. Lastly, the conclusion of the study and its practical implications are presented in Section 5.

2. Literature Review

The patient experience has emerged as an important indicator of the quality of healthcare and patient-oriented care (Edgman Levitan & Schoenbaum, 2021; Wong et al., 2020). With the constant evolution of health care systems, the studies about patient experience, satisfaction, and quality of healthcare services have grown significantly since 2020, which was influenced by the operational challenges, staff shortages, and changing expectations of the patients (Baránková et al., 2022). There has been a greater effort from researchers in order to learn about the factors influencing patients' opinions of the patient's opinion about the provided healthcare services (Simpson et al., 2022). Literature related to patient experience provides several perspectives, such as service quality, patient journey, healthcare operations, communication, digital healthcare, and service recovery (Oben, 2020). The literature also states that patient experience does not take place in a single occurrence but rather through the entire course of interaction related to healthcare (Rahman et al., 2020). These interactions include appointment, registration, waiting, consultation, diagnostic, and treatment methods, discharge, and post-treatment interactions (Jiamsanguanwong et

al., 2022). All these interactions are involved in assessing healthcare services, and patients tend to evaluate their experience with healthcare as a continuing experience rather than separate occurrences (Ozcelik et al., 2021). Research indicates that experiences, whether positive or negative, at the touchpoints play an important role in shaping perceptions about subsequent interactions (Crubezy et al., 2023). Rahman et al. (2020), in their mixed-methods study based on experience surveys involving 609 patients in the UK, discovered that admission, first assessment, and discharge were touchpoints that involved an emotional aspect wherein negative experiences were prevalent, and hence indicate that both the start and the end of a patient journey hold more emotional value compared to what happens in between. In the same way, Cunha et al. (2026), in their qualitative journey mapping involving nine patients' journeys in Portugal, have shown the existence of "weak signals," which include sensory overload and digital confusion, not measured by traditional satisfaction surveys, suggesting that standardized tools tend to systematically under-represent precisely the frictions which form the experiences of patients. These findings collectively suggest that experiences of patients are not uniformly distributed across their healthcare journeys, but rather are clustered around certain friction points, thus providing initial justification for touchpoint-based assessment of patients.

The literature consistently highlights the relevance of operational, administrative, and interpersonal factors in creating patient experience. Rockwell et al. (2024) used a combination of qualitative interviews (n = 22) and quantitative survey responses from 255 respondents in the US, and demonstrated that administrative "sludge," duplicated forms, duplicate data entry, and ambiguous instructions were associated with delays in cancer screening and lower trust levels, thus proving that friction embedded in back-office systems can manifest itself in poor clinical outcomes. Servetkienė et al. (2023) performed a cross-sectional study using 1,033 respondents in Lithuania and determined that organizational accessibility, which includes easy scheduling and physical accessibility of care, was the most important predictor of quality of primary care. However, Cheon et al. (2024), studying 2,005 U.S. hospitals, have reported that satisfaction is better explained by quality of interaction with frontline staff compared to coordination factors, demonstrating the significance of staff interaction in the overall level of satisfaction. Similarly, Ajam et al. (2023), through the study involving 69,319 patients undergoing radiological examination, found that empathy, together with logistical aspects such as the registration process and waiting area quality, were the main determinants of the experience. In this series of research, operational variables play an important role, but they are always considered as additive elements of an index of satisfaction and not possible points of failure that can trump other good experiences.

In addition to the operational attributes in healthcare provision, studies that focus on the importance of communication demonstrate that high-quality interpersonal relations can compensate for poor operational features, which further supports the notion that the relational aspect of care has its own particular importance in the evaluation process. As Turcotte-Tremblay et al. (2023) note, in their survey of 13,149 caregivers from five low- and middle-income countries, the adequacy of explanation turned out to be the most powerful predictor of satisfaction, outweighing structural features such as facility infrastructure or wait time. In the survey conducted by Bashir et al. (2023) involving 78 out of 109 bariatric-tourism patients from Pakistan, the lack of waiting along with low cost became the factors that made 92 percent of patients satisfied. This research shows that in some particular service settings, some critical factors rather than the average combination of attributes can significantly influence the evaluation process.

Another stream includes interventions utilizing digital and process tools to directly address identified pain points in patient experience. Gerbutavicius et al. (2024) find that a perioperative educational application enhances informational support and patient satisfaction in 297 German patients undergoing surgery; their findings address the type of communication gap discussed above via a more scalable digital medium. Wang et al. (2025) demonstrate the effect of an intelligent guidance system on reducing the waiting time and increasing satisfaction through the analysis

of outpatient processes in China, which addresses the logistical pain points noted by Rockwell et al. (2024) and Ajam et al. (2023). Sallam et al. (2025) report a 19-month improvement initiative within a public hospital in the UAE and show that process improvements decrease waiting time and increase both Net Promoter Score and SERVQUAL measures, proving that multi-year process optimization can indeed make a difference in standard satisfaction metrics. Interventions discussed above enhance patient outcomes, but they are almost entirely assessed using compensatory, averaging metrics instead of a failure model showing whether the intervention eliminates the disproportionate failure.

Collectively, the reviewed studies depict that patient experience is consistently associated with specific critical touchpoints such as admission and discharge (Rahman et al., 2020), process of administration (Rockwell et al., 2024), communication (Turcotte-Tremblay et al., 2023), and cost or waiting time (Bashir et al., 2023), but still none test whether these failures operate through a non-compensatory or weakest-link logic rather than being integrated into an average score of satisfaction. This shows a significant gap in methodological approach, as qualitative and descriptive evidence has shown that the causes of individual failures have a disproportionately large impact on the field but cannot be identified through regression-based, compensatory models which are prevalent in the field. Also, most of the studies treat touchpoints descriptively instead of as a connected sequence in which an earlier failure can propagate forward across the patient journey (Crubezy et al., 2023; Cunha et al., 2026). Lastly, recovery of service and efforts of process optimization are shown to improve outcomes (Gerbutavicius et al., 2024; Sallam et al., 2025; Wang et al., 2025), yet there is no empirical evidence on whether such efforts can effectively offset the consequences of a critical touchpoint failure on overall satisfaction, or whether they can only mitigate the overall impact while the disproportionate impact of the critical touchpoint failure persists. This study aims to bridge these gaps by proposing and testing an integrated compensatory-non-compensatory framework of patient experience formation, combining structural modeling with necessity-based and fuzzy aggregation logic, thereby providing a methodological and theoretical alternative to the compensatory assumptions that have been prevalent in the literature.

3. Data and Methodology

3.1. Data Collection Procedure

This research considered adult individuals who have accessed healthcare services in the Kingdom of Saudi Arabia during the last six months. The sample size was determined by using two approaches. The first approach utilized a priori power analysis using G*Power 3.1 for the PLS-SEM structural model, which assumes a medium effect size ($f^2 = 0.15$), a significance level of 0.05, a statistical power of 0.95, and four predictors. This analysis suggested a minimum required sample size of 129 participants (Faul et al., 2009; Cohen, 1988). The second method employed Cochran's formula to account for the large and unknown population size. In this approach, a 95% confidence level, a 5% margin of error, and a 50% population proportion were considered. Accordingly, a required sample size for this method is 385 (Cochran, 1977; Krejcie & Morgan, 1970). The large sample size was selected to ensure enough variability for further NCA and fuzzy-set analysis (Dul, 2016; Pappas & Woodside, 2021).

The data were collected using an online questionnaire which was distributed electronically through SMS and WhatsApp links. This questionnaire was developed as part of a broader research program and designed for using across several related studies of patient evaluation across healthcare touchpoints. Prior using it underwent expert review, pilot testing, and assessment of its validity and reliability. The questionnaire used in the study is provided as Supplementary File 1.

This study used a convenience sampling method, and the participation of respondents was voluntary. The eligible respondents were adults who had recently experienced healthcare services in Saudi Arabia. The data collection was conducted during various time periods to reduce potential bias due to timing. Then, the collected data were analyzed using PLS-SEM analysis, and once the necessary conditions were identified through NCA, the fuzzy non-compensatory model was developed.

3.2. Analytical Models

3.2.1. PLS-SEM Compensatory Model

The study utilizes Partial Least Squares Structural Equation Modeling (PLS-SEM) to analyze compensatory association within the hierarchical model (Hair et al., 2017; Sarstedt et al., 2019). For the assessment of the measurement model, criteria for reflective lower-order constructs are utilized as follows: indicator loadings should be higher than 0.7; internal consistency reliability is evaluated by using Cronbach's alpha and composite reliability (values higher than 0.7 are considered acceptable); convergent validity is indicated when the average variance extracted (AVE) is higher than 0.5; and discriminant validity is confirmed when the heterotrait-monotrait ratio (HTMT) is less than 0.85 (Hair et al., 2019).

For the analysis of the structural model, path coefficients are computed, and the significance of coefficients is evaluated by employing the bootstrapping method using 10,000 subsamples (Hair et al., 2019). Some of the crucial metrics include the coefficient of determination (R^2) of the endogenous constructs and effect sizes (f^2) that reveal the effect of the predictor on the outcome (Hair et al., 2017). Lastly, IPMA is performed to identify key management areas based on the comparison of the total effects (importance) of constructs to their average latent variable scores (performance) (Sarstedt et al., 2024).

In order to verify the reliability of the research, the robustness of the compensatory analysis is tested through the comparison of the PLS-SEM and the subsequent NCA and fuzzy aggregation techniques. Consistency across methods is seen as evidence of reliable findings, while differences are explained based on the unique reasoning behind each method (Dul, 2016; Hair et al., 2017).

3.2.2. Necessary Condition Analysis Model

After the PLS-SEM compensatory model, the study involves using Necessary Condition Analysis (NCA) to determine which conditions must be met at a minimum level for a desired outcome to happen (Dul, 2016). This analysis checks whether the four main service dimensions and their underlying sub-dimensions are essential for achieving high Overall Patient Satisfaction (Dul et al., 2023). In NCA, the effect sizes (d) are classified as small when d is less than 0.1, medium when it is between 0.1 and 0.3, large when it is between 0.3 and 0.5, and very large when it is 0.5 or higher (Dul, 2016). Bottleneck tables are built to illustrate the lowest possible degree of each condition required for each level of outcome (Dul et al., 2023). The principal technique applied is CR-FDH (ceiling regression with fixed dummy), while CE-FDH (ceiling envelope with fixed dummy) is applied as an alternative for sensitivity checks (Dul, 2016; Troiville et al., 2025). Permutation tests are employed to assess the significance of necessity effects (Becker et al., 2026).

3.2.3. Fuzzy Non-Compensatory Model

Based on the findings from the PLS-SEM analysis and the use of Necessary Condition Analysis (NCA), a fuzzy non-compensatory model was created to determine the conditions required for achieving a higher level of Overall Patient Satisfaction (Ragin, 2006; Ragin, 2008). First, a calibration process was used to convert the raw scores from a five-point evaluative scale (where 1 = Poor to 5 = Excellent) into fuzzy membership scores between 0 and 1 (Schneider &

Wagemann, 2012). This calibration method includes the NCA-derived bottleneck thresholds for the sub-dimensions that are considered necessary, while still keeping the original meaning of the scale anchors (Lafuente et al., 1998).

Next, MIN aggregation was used as the main non-compensatory rule. With this rule, the fuzzy score for Overall Patient Satisfaction is based on the lowest membership score among the calibrated necessary sub-dimensions (Dubois, 2010; Hasan et al., 2023). This approach follows a 'weakest-link' logic, meaning that the worst-performing critical condition limits the overall evaluation outcome (Zhao et al., 2025). The strict fuzzy aggregate is calculated as:

$$\mu_i^{\text{MIN}} = \bigwedge_{j=1}^m \mu_{ij}^{\text{cap}} = \min_{j=1, \dots, m} \left\{ \mu_{ij}^{\text{cap}} \right\}, \quad \mu_{ij}^{\text{cap}} \in [0,1] \quad (1)$$

Additionally, Soft-MIN aggregation was utilized as a sensitivity check. In contrast to the strict MIN rule, the Soft-MIN approach provides a certain flexibility in terms of compensation between the required conditions yet retains the high penalty for bad performance (Castillo, 2007; Elamir et al., 2024). The applied version of the Soft-MIN rule is formulated as follows:

$$\mu_i^{\text{SoftMIN}} = \begin{cases} 0, & \text{if } \min_j \left(\mu_{ij}^{\text{cap}} \right) = 0, \\ \left[\frac{1}{m} \sum_{j=1}^m \left(\mu_{ij}^{\text{cap}} \right)^{-20} \right]^{-1/20}, & \text{if } \min_j \left(\mu_{ij}^{\text{cap}} \right) > 0. \end{cases} \quad (2)$$

In order to test the model's robustness and stability, the model was evaluated under alternative calibration thresholds and compared using both MIN and Soft-MIN aggregation rules. It was also validated using a separate sample from a single medical center. In this validation process, the NCA-derived thresholds and fuzzy aggregation rules were applied without recalibrating or re-estimating, thus avoiding circular reasoning. This provides an evaluation of whether the identified non-compensatory logic and weakest-link relationship remain consistent in a different healthcare setting (Ragin, 2008; Cheah et al., 2018).

4. Results and Discussion

4.1. PLS-SEM Structural Model Analysis

The national data set of about 772 respondents was assessed using PLS-SEM analysis, which proceeds sequentially from the model of reflective measurement to the direct structural association between patient experience and Overall Patient Satisfaction and IPMA, in accordance with standard practices (Hair et al., 2017; Hair et al., 2019).

Table 1 shows that the values of all 52 outer loadings exceeded the suggested minimum of 0.708, varying from 0.866 to 0.976 and being significant at $p < 0.001$, which is an indication of the reliability of the indicators (Hair et al., 2017; Hair et al., 2019). Reliability, internal consistency, and validity measures were also confirmed, with Cronbach's α (0.934 to 0.978), ρ_A (0.936 to 0.978), and composite reliability (0.953 to 0.984) all being higher than the threshold of 0.70, and AVE values (0.836 to 0.939) exceeding the 0.50 benchmark, indicating convergent validity. Discriminant validity was verified by HTMT ratios, which met the recommended threshold levels. Collectively, these findings validate the reliability, internal consistency, and convergent and discriminant validity for the reflective constructs.

With respect to the structural model illustrated in Table 2, the construct of Patient Experience proved to have a strong, positive, and statistically significant influence on Overall Patient Satisfaction ($\beta = 0.956$, $p < 0.001$), which is consistent with Park et al. (2022). The strength of this relationship was further evidenced through the absence of structural

collinearity ($VIF = 1.000$). Patient Experience explained 91.4% of the variance in Overall Patient Satisfaction ($R^2 = 0.914$), with an effect size ($f^2 = 10.580$), indicating a strong ability to explain the results.

Lastly, IPMA was performed on Overall Patient Satisfaction as the target construct (Henseler et al., 2016; Otok et al., 2026), utilizing a rescaled 0–100 performance scale and identifying the constructs that have high importance and low performance (Sarstedt et al., 2024). Table 3 shows that Patient Experience was highly important (0.956) but underperforming comparatively (65.37) at the higher-order level. Out of four major dimensions, Communication and Patient Provider Interaction had achieved the highest importance (0.355), while Operational and Administrative Process Experience received the second-highest importance (0.250) and the lowest performance (61.48), which makes it the clearest improvement priority. This is consistent with prior IPMA-based healthcare studies, which similarly identified procedural and operational dimensions as priority areas requiring managerial attention due to their combination of high importance and comparatively weaker performance (Sidik & Antonio, 2024). On the other hand, Responsiveness was the most important (0.176) at the sub-dimension level, followed by Operational Coordination (0.162) and Post-Visit Evaluation (0.145). Specifically, the dimension with high importance and low performance is Operational Coordination (63.11), indicating a clear opportunity for enhancement. While Waiting Time Experience had the lowest performance (54.70) and low importance (0.033), suggesting that low performance does not necessarily indicate priority alone, a pattern also observed in prior healthcare satisfaction research where wait-time dissatisfaction was found to be shaped more by interpersonal and communication factors than by duration itself, thereby limiting its standalone priority weight (Mathews et al., 2015). These underperforming areas were subsequently examined through Necessary Condition Analysis to determine whether they function as necessary bottlenecks.

Table 1
Reflective Measurement Model Assessment

Construct	Outer Loading Range	Cronbach's α	ρ_A	ρ_C	AVE
Pre-Visit Evaluation	0.866–0.954	0.934	0.936	0.953	0.836
During-Visit Evaluation	0.892–0.959	0.949	0.954	0.963	0.868
Post-Visit Evaluation	0.870–0.952	0.936	0.937	0.954	0.839
Waiting Time Experience	0.915–0.946	0.952	0.953	0.965	0.874
Administrative Procedures	0.953–0.971	0.973	0.973	0.980	0.925
Operational Coordination	0.917–0.943	0.952	0.952	0.965	0.874
Clarity of Information	0.960–0.972	0.977	0.977	0.983	0.935
Empathy and Respect	0.938–0.970	0.970	0.971	0.978	0.917
Responsiveness	0.958–0.973	0.976	0.976	0.982	0.932
Digital Experience	0.946–0.967	0.970	0.970	0.978	0.917
Physical Environment	0.911–0.951	0.946	0.948	0.961	0.861
Accessibility and Convenience	0.884–0.947	0.935	0.936	0.954	0.838
Overall Patient Satisfaction	0.962–0.976	0.978	0.978	0.984	0.939
<i>Note. All outer loadings were statistically significant at $p < .001$. α = Cronbach's alpha; ρ_A = Dijkstra–Henseler's rho; ρ_C = composite reliability; AVE = average variance extracted. Values are rounded to three decimal places.</i>					

Table 2
Structural Model Assessment and Direct Effect Results

Relationship	Inner VIF	β	p	f^2
Patient Experience → Overall Patient Satisfaction	1.000	0.956	< 0.001	10.580
<i>Note. β = standardized path coefficient. For Overall Patient Satisfaction, $R^2 = 0.914$.</i>				

Table 3
Importance–Performance Map Analysis for Overall Patient Satisfaction

Analytical level	Construct or dimension	Importance	Performance
Stage 3: Higher-order construct	Patient Experience	0.956	65.37
Stage 3: Main dimensions	Communication and Patient–Provider Interaction	0.355	66.49
	Operational and Administrative Process Experience	0.250	61.48
	Journey Stages Experience	0.245	66.28
	Digital and Environmental Experience	0.164	67.50
Stage 1: Diagnostic sub-dimensions	Responsiveness	0.176	65.39
	Operational Coordination	0.162	63.11
	Post-Visit Evaluation	0.145	64.11
	Physical Environment	0.125	67.74
	Clarity of Information	0.120	66.20
	During-Visit Evaluation	0.116	68.56
	Empathy and Respect	0.075	69.02
	Administrative Procedures	0.067	62.37
	Digital Experience	0.036	63.74
	Waiting Time Experience	0.033	54.70
	Accessibility and Convenience	0.014	69.89
	Pre-Visit Evaluation	0.002	61.23

Note. Importance represents the total effect on Overall Patient Satisfaction; performance is expressed on a rescaled 0–100 scale. Within each analytical level, dimensions are ordered by importance.

4.2. Necessary Condition Analysis

As illustrated in Table 4, in the case of the main dimension level, there were three dimensions exhibiting moderate necessity effects under the primary specification of CR-FDH: the Experience of Journey Stages ($d = 0.200$, $p < 0.001$), Communication and Patient-Provider ($d = 0.189$, $p < 0.001$), and Digital and Environmental ($d = 0.181$, $p < 0.001$) (Troiville et al., 2025). These effect sizes fall within the $0.1 \leq d < 0.3$ range classified as a medium/moderate necessary condition, consistent with the effect size guidelines established for NCA (Dul, 2016). For an Overall level of Patient Satisfaction of 75, their corresponding performance bottleneck requirements were 39.43, 32.23, and 31.06, respectively. The Operational and Administrative Process experience also showed a statistically significant effect ($d = 0.037$, $p < 0.001$), but its small effect size and low bottleneck requirement (6.73) indicated weak practical necessity, falling below the 0.1 threshold typically used to distinguish trivial from meaningful necessary conditions (Dul, 2016). These main-dimension findings provided domain-level evidence and were not included in the subsequent NCA-informed Fuzzy Aggregation Model.

At the sub-dimension level, 12 lower-order service constructs are assessed by NCA as potential necessary conditions that lead to high levels of Overall Patient Satisfaction. As shown in Table 5, CR-FDH was employed as the primary ceiling-line approach, with CE-FDH used to ensure robustness (Dul et al., 2023). Necessary effects, statistical significance, and interpretability requirements have been used as evaluation criteria to identify necessary conditions to proceed to the next stage, which is the NCA-informed Fuzzy Aggregation Model (Dul, 2016). The findings revealed a wide range of necessity strength across the 12 sub-dimensions. Pre-Visit Evaluation, During-Visit Evaluation, Post-Visit Evaluation, and Digital Experience did not show any noticeable necessity effects ($d = 0.000$). However, the other eight sub-dimensions had statistically significant necessity effects. Among these, Accessibility and Convenience had the strongest necessity effect ($d = 0.210$), which is considered medium, followed by Responsiveness ($d = 0.082$) and Physical Environment ($d = 0.063$). This result aligns with the research conducted by Ziaei et al. (2011), who also noted accessibility as one of the most influential factors for patients' overall satisfaction across healthcare service dimensions. The rest of the significant conditions showed smaller necessity effects. These results highlight the factors that need further attention in the NCA-informed Fuzzy Aggregation Model.

Table 4
Main-Dimension Necessary Condition Analysis Results for Overall Patient Satisfaction

PN	Main Service Dimension	CR-FDH d	Effect	Permutation p	CE-FDH d	CR-FDH Requirement at OPS = 75	Decision
PN1	Journey Stages Experience	0.200	Medium	< 0.001	0.198	$X \geq 39.43$	Supported
PN2	Operational and Administrative Process Experience	0.037	Small	< 0.001	0.047	$X \geq 6.73$	Supported, but practically weak
PN3	Communication and Patient–Provider Interaction	0.189	Medium	< 0.001	0.204	$X \geq 32.23$	Supported
PN4	Digital and Environmental Experience	0.181	Medium	< 0.001	0.206	$X \geq 31.06$	Supported

Table 5
Sub-Dimension Necessary Condition Analysis Results for Overall Patient Satisfaction

PN	Service Sub-Dimension	CR-FDH d	Effect	Permutation p	CE-FDH d	Proposition Decision
PN1a	Pre-Visit Evaluation	0.000	No effect	N/A	0.000	Not supported; not retained
PN1b	During-Visit Evaluation	0.000	No effect	N/A	0.000	Not supported; not retained
PN1c	Post-Visit Evaluation	0.000	No effect	N/A	0.000	Not supported; not retained
PN2a	Waiting Time Experience	0.007	Small	< 0.001	0.008	Supported as a small outcome-specific necessity pattern; retained in the expanded graded specification
PN2b	Administrative Procedures	0.002	Small	< 0.001	0.004	Supported as a small outcome-specific necessity pattern; retained in the expanded graded specification
PN2c	Operational Coordination	0.016	Small	< 0.001	0.031	Supported as a small outcome-specific necessity pattern; retained in the expanded graded specification
PN3a	Clarity of Information	0.012	Small	< 0.001	0.023	Supported as a small outcome-specific necessity pattern; retained in the expanded graded specification
PN3b	Empathy and Respect	0.035	Small	< 0.001	0.069	Supported as a small outcome-specific necessity pattern; retained in the expanded graded specification
PN3c	Responsiveness	0.082	Small	< 0.001	0.095	Supported as a small outcome-specific necessity pattern; retained in the expanded graded specification
PN4a	Digital Experience	0.000	No effect	N/A	0.000	Not supported; not retained
PN4b	Physical Environment	0.063	Small	< 0.001	0.075	Supported as a small outcome-specific necessity pattern; retained in the expanded graded specification
PN4c	Accessibility and Convenience	0.210	Medium	< 0.001	0.235	Supported; retained in the expanded graded specification and met the $d \geq .10$ interpretive benchmark.

4.3. NCA Informed Fuzzy Aggregation Model Analysis

Eight service sub-dimensions- Waiting Time Experience, Administrative Procedures, Operational Coordination, Clarity of Information, Empathy and Respect, Responsiveness, Physical Environment, and Accessibility and Convenience- were retained in the graded NCA-informed Fuzzy Aggregation Model based on the necessity effects reported in Section 4.2. The main service dimensions were kept as higher-level NCA findings but were not used as inputs in the

fuzzy aggregation model. These retained sub-dimensions were transformed into satisfaction-supporting capacities of individual conditions by applying their CR-FDH ceiling functions (Dul et al., 2023), while, for each participant, the level of satisfaction was computed using the estimated ceiling function for each condition, restricted to the scale of 0-100. These individual condition-specific capacities were aggregated by applying the MIN operator such that the worst-performing condition determines the capacity to satisfy Overall Patient Satisfaction (Dubois, 2010; Ragin, 2006). CR-FDH served as the primary method, with corresponding results of CE-FDH reviewed as part of the sensitivity analysis (Dul et al., 2023; Becker et al., 2026).

For the sample of independent single-site (N = 626), the eight retained conditions were converted into satisfaction-support capacities and aggregated by means of the Strict MIN operator (Table 6) and (Table 7). The average of the joint fuzzy satisfaction-support membership was 0.896 (SD = 0.267), with a median and range of 1.000 and 0.000–1.000, respectively. The Soft-MIN sensitivity specification yielded a similar average membership of 0.906 with SD equal to 0.264, with the same median and range, demonstrating that the change in the aggregation method had little influence on the overall results. In the context of the 0-100 outcome-support scale, the Strict MIN approach yielded the average supported satisfaction capability value of 93.41 (SD = 18.32), a median of 100, and a range from 21.51 to 100. As for the total number of cases, 575 cases (91.85%) reached a joint support level of at least 75, while 51 cases (8.15%) scored below this threshold. Whereas the Strict MIN specification responses show that 155 cases (24.76%) had actively limiting conditions, while 471 cases (75.24%) had no actively limiting conditions because all eight retained conditions supported the maximum potential yield. The findings of the Soft-MIN method were largely similar and support the consistency of the weakest-link aggregation approach.

Table 6
CR-FDH Parameters and NCA-Informed Capacity Functions for the Retained Necessary Conditions

Retained Necessary Condition	CR-FDH <i>d</i>	Slope β_j	Intercept α_j	Capacity Function <i>Cij</i>	First Reported Positive Requirement in the 5-Point Bottleneck Grid
Waiting Time Experience	0.007	1.1690	86.8701	$clip(86.8701 + 1.1690X_{ij})$	OPS 90: $X \geq 2.68$
Administrative Procedures	0.002	0.9898	93.7090	$clip(93.7090 + 0.9898X_{ij})$	OPS 95: $X \geq 1.30$
Operational Coordination	0.016	0.4938	87.5340	$clip(87.5340 + 0.4938X_{ij})$	OPS 90: $X \geq 4.99$
Clarity of Information	0.012	0.6630	87.6180	$clip(87.6180 + 0.6630X_{ij})$	OPS 90: $X \geq 3.59$
Empathy and Respect	0.035	0.2211	87.6180	$clip(87.6180 + 0.2211X_{ij})$	OPS 90: $X \geq 10.77$
Responsiveness	0.082	2.1820	40.0369	$clip(40.0369 + 2.1820X_{ij})$	OPS 75: $X \geq 16.02$
Physical Environment	0.063	0.2958	80.6739	$clip(80.6739 + 0.2958X_{ij})$	OPS 85: $X \geq 14.62$
Accessibility and Convenience	0.210	1.4695	21.5064	$clip(21.5064 + 1.4695X_{ij})$	OPS 75: $X \geq 36.40$

Table 7
Strict MIN and Soft-MIN Aggregation Results under the Primary CR-FDH Specification

Panel A. Fuzzy Satisfaction-Support Membership							
Aggregation	Mean (SD)	Median	Range	< 0.50, n (%)	≥ 0.50, n (%)	At 0, n (%)	At 1, n (%)
Strict MIN	0.896 (0.267)	1.000	0.000– 1.000	51 (8.15)	575 (91.85)	42 (6.71)	471 (75.24)
Soft-MIN (p = -20)	0.906 (0.264)	1.000	0.000– 1.000	51 (8.15)	575 (91.85)	42 (6.71)	471 (75.24)
Panel B. Satisfaction-Support Capacity (0–100)							
Aggregation	Mean (SD)	Median	Range	< 75, n (%)	≥ 75, n (%)		
Strict MIN	93.413 (18.316)	100.000	21.506– 100.000	51 (8.15)	575 (91.85)		
Soft-MIN equivalent	95.309 (13.225)	100.000	50.000– 100.000	51 (8.15)	575 (91.85)		

5. Conclusion

This study explored whether patients' views on their healthcare experiences can be better explained by either compensatory or non-compensatory ways of evaluating their experiences across various points of contact with healthcare services. The research used a step-by-step analysis approach that combined Partial Least Squares Structural Equation Modeling (PLS-SEM), Necessary Condition Analysis (NCA), and a fuzzy aggregation model informed by NCA. The results show that simply looking at average relationships is not enough to fully understand patient experience. PLS-SEM found strong compensatory links between different service aspects and showed that Patient experience is a strong predictor of Overall Patient Satisfaction ($\beta = 0.956$, $p < 0.001$, $R^2 = 0.914$).

NCA added another layer by showing that certain service conditions act as essential requirements rather than just factors that influence outcomes. Eight sub-dimensions were found to be necessary for achieving high Overall Patient Satisfaction, emphasizing the need for minimum performance levels at key points in healthcare delivery. The fuzzy aggregation model, which was informed by NCA, then showed how poor performance in one critical area can limit overall satisfaction, even if other areas are performing well.

Combining these methods contributes to the study of patient experience by showing how using both compensatory and non-compensatory approaches can provide a more complete picture. PLS-SEM helps identify influential service factors; NCA highlights essential conditions, and the fuzzy aggregation model shows how weaknesses in critical areas can affect overall outcomes. This combined view gives healthcare organizations a better way to focus on their improvement efforts rather than just relying on overall averages or satisfaction scores. It can also help them identify specific service issues and potential warning signs in healthcare delivery.

However, the results should be considered within the context of this study. The thresholds identified through NCA and the fuzzy aggregation model were based on a national sample from Saudi Arabia and tested with an independent single-site sample. Therefore, the framework should be seen as an example that is sensitive to context rather than a universally applicable model. Future research could examine this framework in different healthcare settings, organizations, and patient groups to test how stable and applicable the necessary conditions and critical thresholds are across various contexts.

Declarations

6.1 Ethics approval and consent to participate

Ethical approval for this study was obtained from the Research Ethics Committee at Effat University (Approval No. RCI_REC/30.June.2026/7-7.1. Exp./1(180)).

6.2 Consent to Participate

Data were collected using an electronic questionnaire. No any personal or identify information was collected from participants. At the beginning of the questionnaire each participant was presented with an electronic informed consent statement explaining the purpose of the study and the voluntary nature of participation. Only participants who provided their electronic consent were able to proceed with and complete the questionnaire.

6.3 Consent for publication

Not Applicable

6.5 Competing interests

The authors declare that they have no competing interests.

6.6 Funding

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

Author Contribution

The author was solely responsible for the conception and design of the study, data collection, methodology, data analysis and interpretation, and preparation of the manuscript.

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Data Availability

The datasets generated and/or analyzed during the current study are available from the corresponding author on reasonable request.

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