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Designing a competency model for the succession of nursing managers, using the Fuzzy Inference System

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ABSTRACT

Background & Aim: Identifying competencies is fundamental for effective succession planning. Studies show that achieving a suitable succession planning model for mid-level nursing managers/supervisors can be helpful in achieving the desired goals of top-level nursing managers/matrons. Thus, this study aimed to design a competency model for the succession of mid-level nursing managers from the perspective of top-level nursing managers using the Fuzzy Inference System.
Methods & Materials: This health services management research was conducted during 2020-2021. Participants in this study included top-level nursing managers/matrons working in the hospitals affiliated with the Tehran University of Medical Sciences. A census sampling method was used in this study with 14 matrons participating as experts. A three-level Fuzzy Inference System was designed by a competency model for mid-level nursing managers/supervisors, using the previous study. Input and output variables were defined, and fuzzy questionnaires were designed using pair-wise comparison matrices to gather expert opinions on fuzzy rules. These rules were analyzed using MATLAB (R 2019 b) software to compare the effect of each criterion on other levels.
Results: The results showed that managerial experience, equipment management, emotional intelligence, influence and impact on others, self-confidence, and strategic thinking in the first Fuzzy Inference System level, as well as management abilities, influencing skills, and leading management development in the second level, were more influential. In the third- level, the perceptual, relational, and technical variables had higher priorities, respectively.
Conclusion: Senior managers could use the proposed model as a checklist/questionnaire to make strategic planning for the succession of nursing managers.

Introduction

Managerial competencies refer to the combination of knowledge, skills, experience, characteristics, and behaviors that a manager needs to achieve organizational goals (1). Managerial competencies are vital for enhancing both individual and organizational performance within healthcare, which leads to improved health outcomes for the community (2). Achieving these competencies requires specific infrastructures, such as the training and development of managers, organizational support, a supportive organizational culture, and the provision of leadership opportunities (3).

Investing in the training and development of healthcare managers is important for successfully implementing reforms in health services managers' competencies (2). In addition, developing managers' competencies is crucial for enhancing productivity within hospitals, which are characterized by their complexity and unique organizational structures. This development is essential as it facilitates efficient management practices and improves overall healthcare service delivery (4).

Senior managers in healthcare organizations need a systematic program aimed at identifying, recruiting, and developing competent managers at different levels (3). Competent nurse managers play an important role in creating a healthy work environment, increasing the satisfaction of both employees and patients, and improving the quality of health services (5). Since managers will inevitably

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leave their positions, it is essential for new managers to possess the requisite skills and knowledge to manage hospitals effectively (3).

As crucial members of healthcare organizations (6), nurse managers require various levels of competency based on their managerial roles and responsibilities. According to the context of the Iranian healthcare system, technical competencies are needed for first-line nursing managers/head nurses, human competencies for mid-level nursing managers/supervisors, and conceptual skills for top-level nursing managers/matrons (7).

According to Pillay (2010), defining a competency model for nursing managers provides a basis for focusing training and development efforts to enhance their practice (8). Without these models, organizations are limited to basic replacement strategies and miss out on proactive talent management (9).

In the context of succession planning, competency models assist organizations in aligning job competencies, identifying high-potential employees, defining critical skills for present and future roles, supporting performance management, clarifying work expectations, creating customized assessments, and developing individual development plans (IDPs). Competency models are fundamental for effective succession planning. Therefore, by using competency models, a structured approach to succession planning can be achieved (9).

Succession planning is an effective tool that provides competent nurses to healthcare organizations and nursing education programs (10). There is a business strategy inherent in succession planning that enables organizations to manage environmental challenges (11) and creates a healthy working environment for employees (12).

Succession planning is not an event but an ongoing process that promotes a culture of excellence, improvement, and innovation in developing future leaders (13). It can enhance transparency in the nursing profession, contribute to the preservation of intellectual capital, and help to achieve organizational vision (14).

Given the global nursing shortage, succession planning has been described as a global necessity (15). Studies in Iran indicate that about half of hospital managers are between 41 and 50 years old, and considering the retirement age of 55-60, many hospitals will have a pressing need for managers, especially mid-level and senior managers, in the coming decade (3). Even if 20,000 new nurses are recruited annually in Iran, it will take at least 5 years to reach the global standard (16). Meanwhile, achieving a succession planning pattern for nursing managers is a fundamental aspect of service delivery (12, 14, 17, 18).

Despite the clear benefits of succession planning, studies show that there is insufficient resource allocation for the proactive development of both current and future nurse managers. Organizations typically rely on inadequate didactic education or on-the-job training, which can lead to ineffective leadership, challenging role transitions, and high turnover rates (11).

Furthermore, other studies indicate that the majority of competency models focus on hospital managers (19-24), top-level nursing managers (6, 25, 26), and first-level nursing managers/head nurses (27,5,1), whereas the competency model for mid-level managers/supervisors has been overlooked. Recent studies demonstrate that it is impractical to achieve the desired goals for the top-level managers/matrons without an appropriate succession planning model for mid-level managers/supervisors (28, 29).

In traditional methods of succession planning, an expert (e.g., senior manager of human resources) typically selects the best candidate after interviewing and analyzing the individual abilities. This method can be subjective and lacks accuracy (30). In contrast, the Fuzzy Inference System (FIS) allows us to study and mathematically formulate vague or imprecise concepts, such as competency, based on fuzzy logic competency (30, 31). However, most of the previous studies have been conducted through multivariate statistical methods, such as factor analysis (2, 8, 24, 32), and non-statistical methods, such as hierarchical analysis (27) or systematic reviews (21, 22, 33, 34).

Fuzzy inference is a method that simulates human reasoning regarding vague concepts vague concepts (such as competency) by using experts' opinions based on If-Then rules (35). Additionally, this method enables sensitivity analysis, which assesses how variations in input variables affect the output variable of the system. This analysis is particularly beneficial for understanding the significance of different inputs and their relative contributions to the outcomes produced (competency) by the fuzzy model (36). Therefore, it can serve as a guide for addressing and modifying these variables to enhance competency (37). To this end, the current study was conducted to design a competency model for succession planning for mid-level nursing managers/supervisors using fuzzy inference systems.

Methods

The current study was conducted in accordance with the health services management research. It was conducted during 2020-2021. The study population included top-level nursing managers/matrons working in hospitals affiliated with the Tehran University of Medical Sciences (TUMS). The census sampling method was used in this study and the study samples included 14 matrons (as experts). A three-level FIS was designed (Figure 1), using the competency model for mid-level nursing managers/supervisors found in the previous study (38).

In the current investigation, the Mamdani fuzzy inference method was used as an analytical process to examine the relationships between input and output variables. Human knowledge and experience play a fundamental role in the Mamdani FIS. The Mamdani-type fuzzy inference process consists of five steps (31):

Step 1. Fuzzifing input variables to convert the crisp input(s) into the linguistic input via membership functions that correspond with the fuzzy rules. The membership functions (MFs), with a range of between 0 and 1, are a degree of membership in the related fuzzy linguistic sets. A fuzzy rule is expressed as an "If-Then" rule. The "If" part is referred to as the antecedent, and the "Then" part is referred to as the consequent.

Step 2. Applying fuzzy logical operations to apply fuzzy operators on the antecedent parts. A fuzzy rule could be expanded using fuzzy operators such as "AND" and "OR".

Step 3. Applying the implication method to implicate the antecedent parts on the consequent part. Before applying the implication method, the weight of each rule (between 0 and 1) should be determined. Generally, the weights will be equal to 1. But in the case of assigning weight to each rule, the weight should be applied to the number obtained from the antecedent parts. The most important implication methods include min and max, which correspond to the fuzzy operation “AND”.

Step 4. Applying the aggregation method to combine fuzzy sets that represent the outputs of rules with a single fuzzy set to make a decision. There are different aggregation methods, including max and sum.

Step 5. Defuzzification of the combined fuzzy set from the aggregation process into a single crisp number. Among the many defuzzification methods, the centroid method is very popular (31).

In this study, to design the fuzzy inference system, the input and output variables with their unique codes were first determined for each level. According to the FIS, the outputs of the first level are the inputs of the second level, and the outputs of the second level are the inputs of the third level (Figure 1).

Then, fuzzy sets and MFs (with a range of between 0 and 100) were defined for the input and output variables. Gaussian MFs were used for input and output variables. Fuzzy If-Then rules were formulated for each level in a way that the rule number depended on several items such as a number of input variables, levels, and linguistic values (37). Five-valued linguistic terms, including very low (VL), low (L), medium (M), high (H), and very high (VH) were utilized in the current investigation, so that at the first, second, and third levels, 750, 75, and 125 rules were formulated, respectively (950 rules, totally).

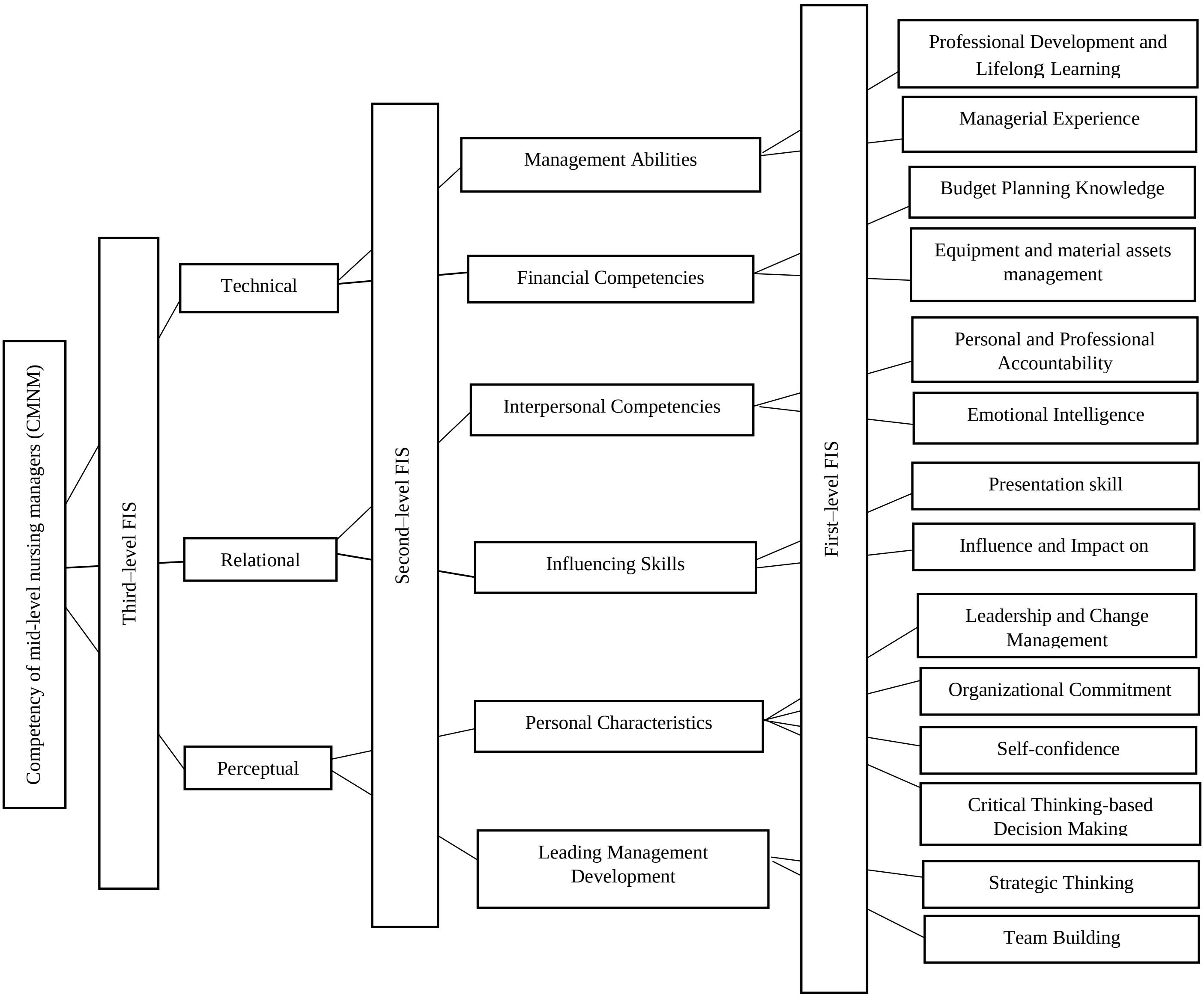

Figure 1. The competency model of mid-level nursing managers/supervisors based on fuzzy inference system

The fuzzy If-Then rules were provided to the experts/matrons as questioners (based on pair-wise comparison matrices) so that, according to the "If" part, they could give their opinions about each of the rules in the "then" part by choosing one of the linguistic values. In the fuzzy questionnaires, the criteria that were in the row and column of these matrices were extracted from the expert's opinions in the previous study. Therefore, the criteria were completely understandable to the experts. Fuzzy questionnaires were distributed and collected in person by the first author among matrons in the hospitals of Tehran University of Medical Sciences.

After collecting the questionnaires, to combine the experts' opinions, the answers experts were entered into MS Excel (version 2016). Also, 8 rules were removed because of inconsistency in the answers, so 942 rules were inputted into MATLAB software (version R 2019b) based on the highest frequency to compare the effect of each criterion on other levels. The study used the AND operator, min implication method, and max aggregation method in its fuzzy rule section, as per Mandeni's inference system. Finally, the fuzzy result of the inference process was defuzzified by the centroid method.

Results

According to the previous study (38), all top-level nursing managers/matrons working in hospitals affiliated with the Tehran University of Medical Sciences participated in this study as experts (14 participants= 100%). All of them were women and the majority (11 people= 78.6%) of them were married. The mean± SD age of the participants and their work experiences in the nursing management positions were 49.89±4.91 and 5.29±4.85 years, respectively. Also, four (28.6%) participants had a B.S. degree, nine (64.3%) had an M.S. degree and one (7.1%) had a Ph.D. degree. To examine the relationships between the variables and their effects on each other, fuzzy If-Then rules and the surface plot were utilized. The results of the fuzzy inference system from the first to the third level are as follows:

Results in the first–level FIS

The input variables included professional development and lifelong learning (MA1), managerial experience (MA2), budget planning knowledge (FC1), equipment and material assets management (FC2), personal and professional accountability (IC1), emotional intelligence (IC2), presentation skill (IS1), influence and impact on others (IS2), leadership and change management (PC1), organizational commitment (PC2), self-confidence (PC3), critical thinking-based decision making (PC4), strategic thinking (LMD1), and team building (LMD2). Each of them was represented by its unique code. The output variables also included management abilities (MA), financial competencies (FC), interpersonal competencies (IC), influencing skills (IS), personal characteristics (PC), and leading management development (LMD). In all outputs at this level, two input variables were utilized, and only in the personal characteristics (PC) output, four input variables were employed (Figure 2).

The surface plot shows the opinion of experts about the effect of each component on other levels and also displays the relationships between fuzzy rules in a general chart. The horizontal axis (X) and vertical axis (Y) represent two input variables, and the height axis (Z) represents the output variable. Also, changes in colors from blue to yellow on the surface plot indicate an increase in values on the Z axis as the output variable in the interactive effect of two input variables.

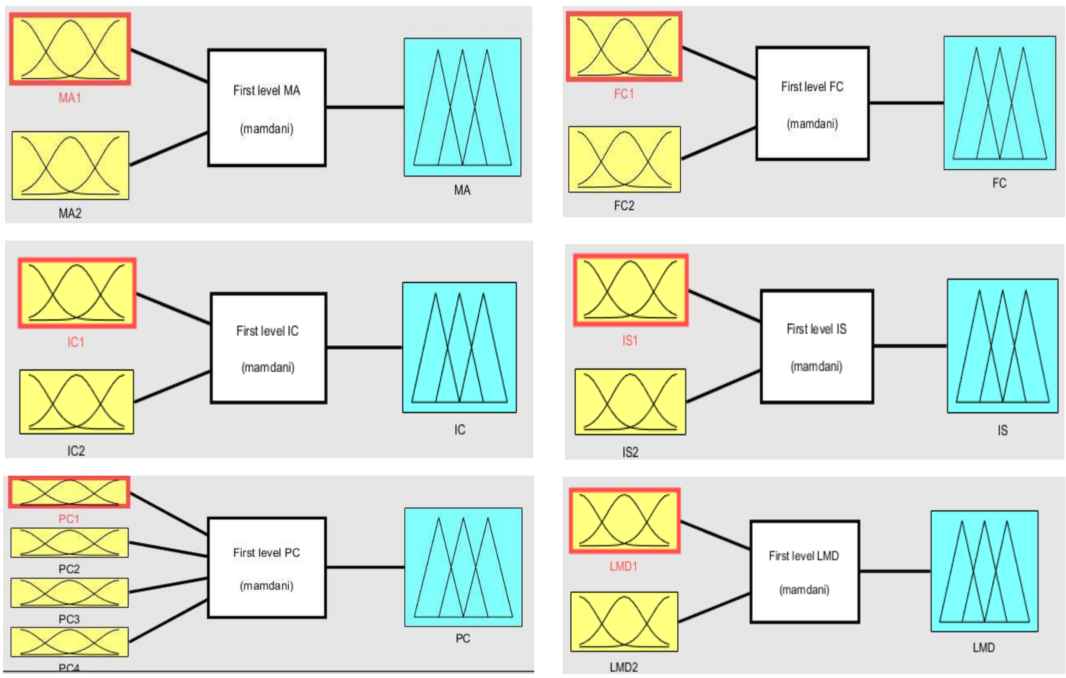

Figure 2. The input variables (MA1, MA2, FC1, FC2, MA1, MA2, IC1, IC2, IS1, IS2, PC1 PC2, PC3, PC4 LMD1, LMD2) and output variables (MA, FC, IC, IS, PC, LMD) in the first-level FIS

The surface plot for two variables (MA1 and MA2) and their effects on the output variable (MA) indicate that, if MA1 tends towards a numerical value of 100 but MA2 reports a numerical value of less than 60, it will be impossible to observe high values in MA (Figure 3). Moreover, this issue was observable in the comparative analysis of rules, particularly in rules 4 and 16 (a). In rule 4, when MA1 and MA2 had VL and H, respectively, the MA value had an L level. In fact, in rule 4, MA2 increased the level of competence in MA, while in rule 16, a VL score did not allow the output (MA) to increase from VL to L level.

4. If (MA1 is VL) and (MA2 is H) then (MA is L) (1)
16. If (MA1 is H) and (MA2 is VL) then (MA is VL) (1)

(a). Rules 4 and 16 to an inference of MA component

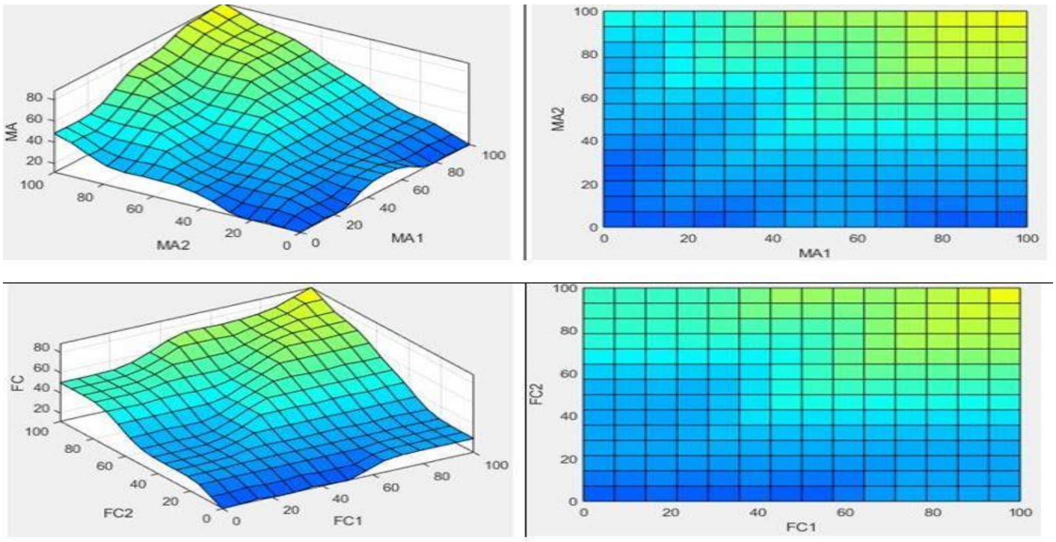

Figure 3. Surface plot of two variables, MA1 and MA2, related to MA, FC1, and FC2 related to FC

The surface plot for FC1 and FC2, and their effect on the FC showed that when FC1 reached 100 value, while FC2 did not report numerical values higher than 50, it was impossible to observe high values on the Z-axis, corresponding to the FC variable (Figure 3). This also was observable in the comparative analysis of rules, especially in rules 3 and 11(b).

3. If (FC1 is VL) and (FC2 is M) then (FC is L) (1)

11. If (FC1 is M) and (FC2 is VL) then (FC is VL) (1)

(b). Rules 3 and 11 to an inference of FC component

The effect of two variables (IC1 and IC2) and their effects on the IC variable indicated that if IC1 tends towards a numerical 100 value, but IC2 reported a numerical value of less than 60, the IC component (IC) will not tend towards higher values (Figure 4). In addition, when the IS2 variable reported low values (less than 40), even with the high values of IS1, the IS component did not display a high numerical value **(**Figure 4). The comparative analysis of rules also indicated these issues, especially in rules 4 and 16 related to IC variable (c), and rules 3 and 11 related to IS variable (d).

4. If (IC1 is VL) and (IC2 is H) then (IC is L) (1)
16. If (IC1 is H) and (IC2 is VL) then (IC is VL) (1)

(c). Rules 4 and 16 to an inference of IC component

3. If (IS1 is VL) and (IS2 is M) then (IS is M) (1)

11. If (IS1 is M) and (IS2 is VL) then (IS is VL) (1)

(d). Rules 3 and 11 to an inference of IS component

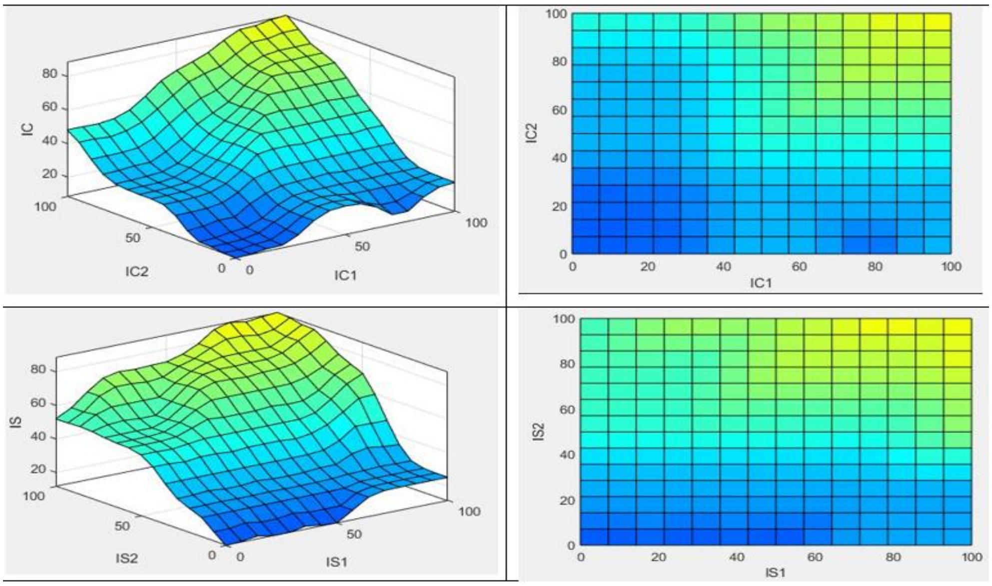

Figure 4. Surface plot of two variables, IC1 and IC2, related to IC, IS1, and IS2 related to IS

However, the influence of the PC component with four input variables was more complex. The effect of the PC1 input variable with three input variables (PC2, PC3, and PC4) and the influence of the PC output variable are shown in Figure 5. The surface plot of the two input variables (PC1 and PC2) and their effect on the PC showed that when PC2 reported the lower values (<40) even if PC1 reported the higher values (>50), the PC did not display a high numerical value (Figure 5). This was also observable in the pair-by-pair comparison of the rules, especially in rules 178 and 277(e).

178. If (PC1 is L) and (PC2 is M) and (PC3 is VL) and (PC4 is M) then (PC is L) (1)

277. If (PC1 is M) and (PC2 is L) and (PC3 is VL) and (PC4 is M) then (PC is VL) (1)

(e). Rules 178 and 277 to infer PC component by comparing PC1 and PC2

The comparison of two variables (PC1 and PC3) and their effect on PC showed that if PC1 tends towards a numerical 100 value, but PC3 reported a numerical value of less than 30, the PC will not tend towards higher values (Figure 5). This was also clear in the pair-by-pair examination of the rules, especially in rules 88 and 327(f).

88. If (PC1 is VL) and (PC2 is H) and (PC3 is M) and (PC4 is M) then (PC is M) (1)
327. If (PC1 is M) and (PC2 is H) and (PC3 is VL) and (PC4 is M) then (PC is VL) (1)

(f) .Rules 88 and 327 to infer PC component from comparing PC1 and PC3

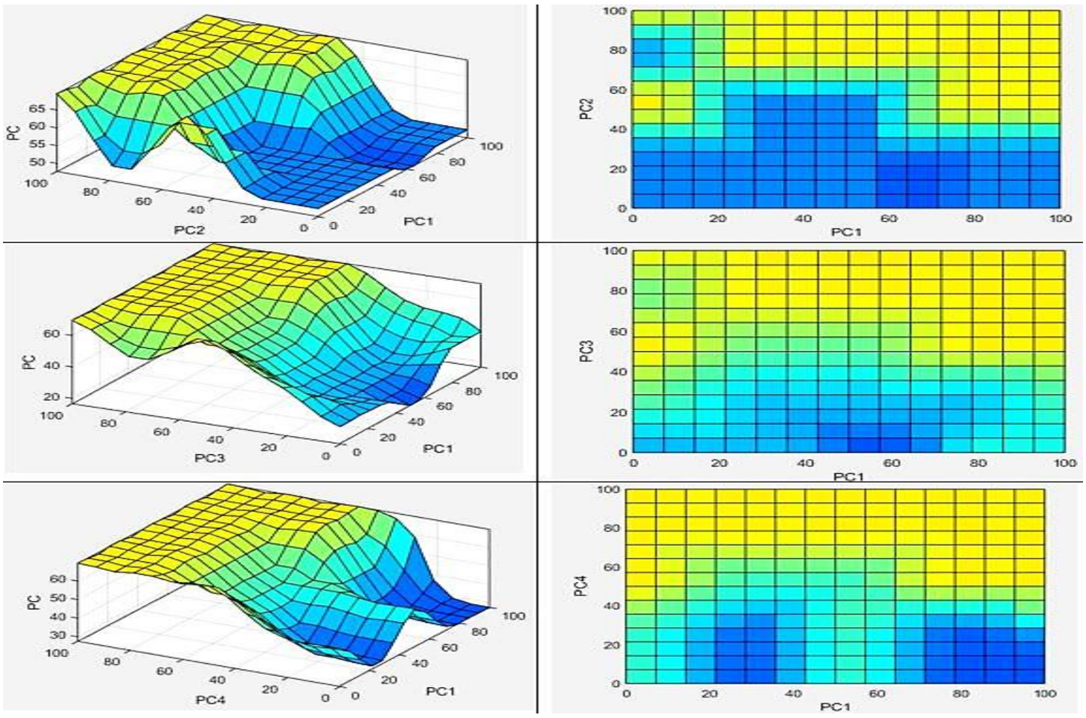

Figure 5. Surface plot of PC1 variable with three variables PC2, PC3, and PC4 related to PC.

The surface plot of two input variables (PC1 and PC4) and their effect on PC indicated that when PC4 reported the lower values (<40) even if PC1 reported the higher values (>50) the PC did not display a high numerical value (Figure 5). The comparative analysis of rules also showed this issue, especially in rules 188 and 434(g).

188. If (PC1 is L) and (PC2 is M) and (PC3 is M) and (PC4 is H) then (PC is H) (1)

434. If (PC1 is H) and (PC2 is M) and (PC3 is M) and (PC4 is L) then (PC is L) (1)

(g). Rules 188 and 434 to infer PC component from comparing PC1 and PC4

The surface plot of two input variables (PC3 and PC2) and their effect on PC displayed that when the PC3 variable reported low values (< 40), even with the high values of PC2 (> 70), the PC did not display a high numerical value (Figure 6). The comparative analysis of rules indicated this importance, especially in rules 10 and 30 (h).

10. If (PC1 is VL) and (PC2 is VL) and (PC3 is L) and (PC4 is VH) then (PC is M) (1)
30. If (PC1 is VL) and (PC2 is L) and (PC3 is VL) and (PC4 is VH) then (PC is L) (1)

(h). Rules 10 and 30 to infer PC component from comparing PC2 and PC3

The comparison of two variables (PC2 and PC4) and their effect on PC indicated that when PC4 reported lower values (< 30) even if PC2 reported higher values (>70), it would be impossible to observe high values in PC (Figure 6). This was also clear in the comparative analysis of rules, especially in rules 467 and 491(i).

467. If (PC1 is H) and (PC2 is H) and (PC3 is H) and (PC4 is VH) then (PC is VH) (1)
491. If (PC1 is H) and (PC2 is VH) and (PC3 is H) and (PC4 is H) then (PC is H) (1)

(i). Rules 467 and 491 to infer PC component from comparing PC2 and PC4

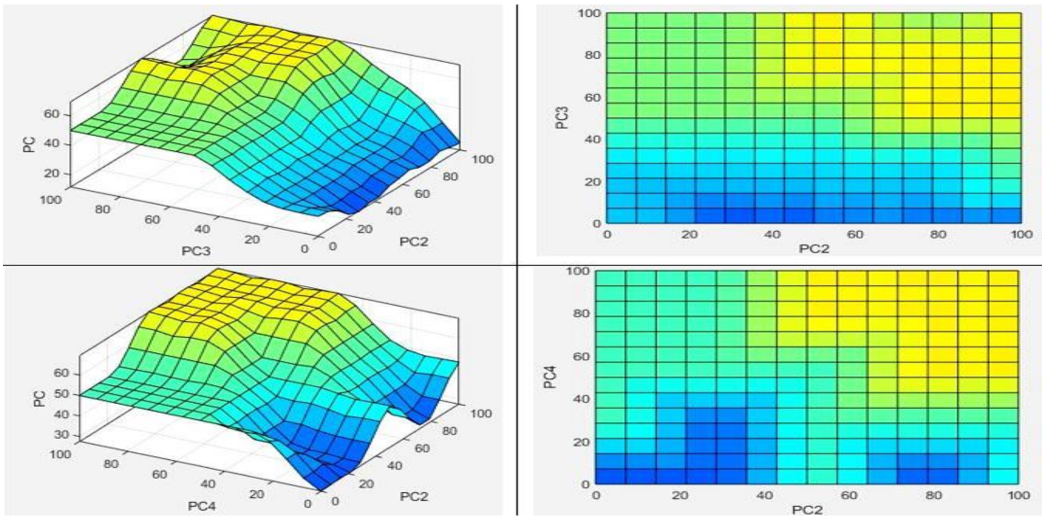

Figure 6. Surface plot of PC2 variable with two variables PC3 and PC4 related to PC.

The surface plot of two input variables (PC3 and PC4) and their effect on PC revealed that when PC3 reported the lower values (< 40), even if PC4 reported the higher values (>70), the PC did not display a high numerical value (Figure 7). This issue was also observable in the comparative analysis of rules, especially in rules 301 and 305 (j).

301. If (PC1 is M) and (PC2 is M) and (PC3 is VL) and (PC4 is L) then (PC is VL) (1)
305. If (PC1 is M) and (PC2 is M) and (PC3 is L) and (PC4 is VL) then (PC is L) (1)

(j). Rules 301 and 305 to infer PC component from comparing PC3 and PC4

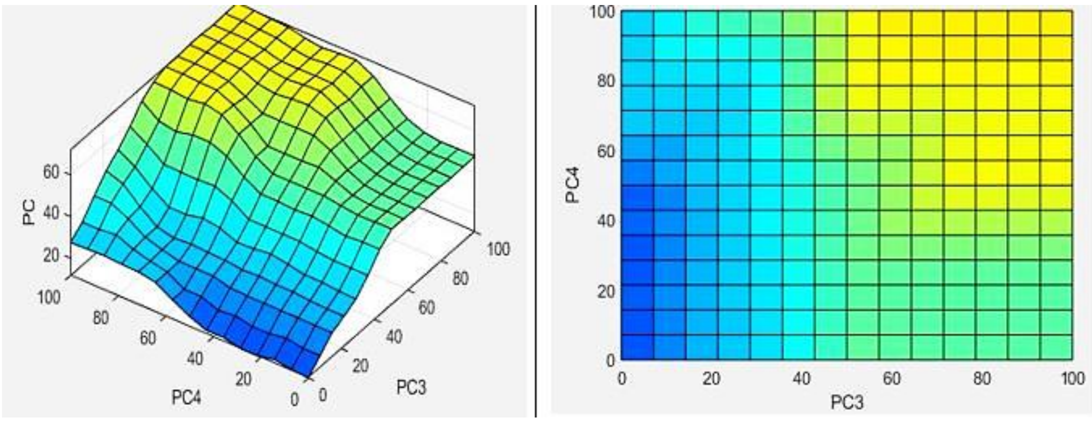

Figure 7. Surface plot of two variables PC3 and PC4 related to PC

The comparison of LMD1 and LMD2 variables and their effect on LMD showed that when the LMD1 represented the lower values (<40), LMD did not show a high numerical value (Figure 8). This was also observable in the comparative analysis of rules, particularly in rules 9 and 17 (k).

9. If (LMD1 is L) and (LMD2 is H) then (LMD is L) (1)
17. If (LMD1 is H) and (LMD2 is L) then (LMD is H) (1)

(k). Rules 9 and 17 to inference of LMD component

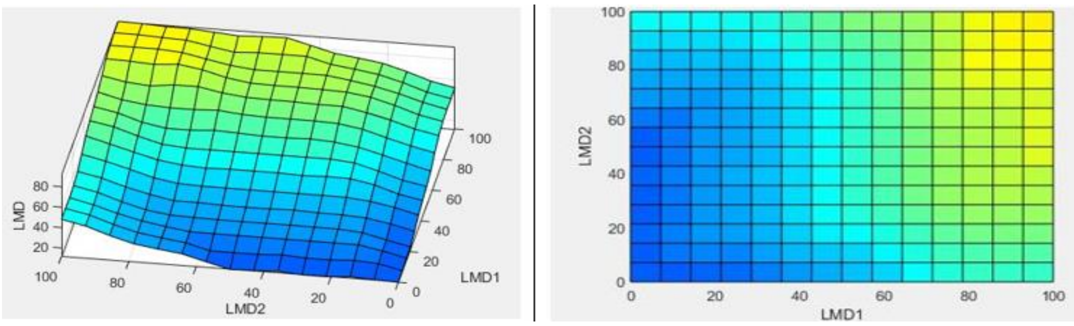

Figure 8. Surface plot of two variables LMD1 and LMD2 related to LMD

Results in the second-level FIS

The second-level input variables included MA, FC, IC, IS, PC, and LMD codes. The output variables also included technical, relational, and perceptual codes (Figure 9). The surface plot of MA and FC related to the technical variable showed that in the low values of MA (< 40), it will be impossible to observe high values in the technical variable (Figure 10). The comparative analysis of rules such as rules 12 and 8 also showed this issue (l).

12. If (MA is M) and (FC is L) then (Technical is M) (1)

8. If (MA is L) and (FC is M) then (Technical is VL) (1)

(l). Rules 12 and 8 to inference of Technical dimension

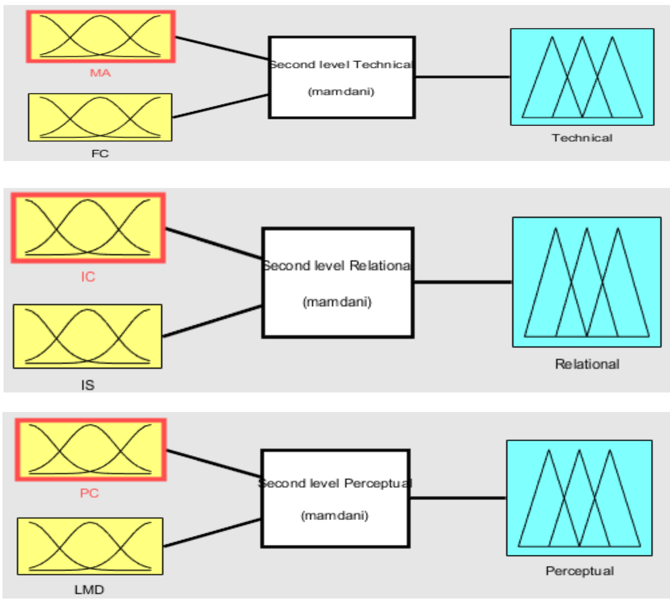

Figure 9. The input variables (MA, FC, IC, IS, PC, LMD) and output variables (Technical, Relational, Perceptual) in the second-level FIS

In addition, the surface plot of IS and IC variables, and their effect on relational variables revealed that in the low values of IS (<50), the relational variable did not display a high numerical value, which was observable in the comparative analysis of rules, particularly in rules5 and 21(m).

5. If (IC is VL) and (IS is VH) then (Relational is M) (1)

21. If (IC is VH) and (IS is VL) then (Relational is VL) (1)

(m). Rules 5 and 21 to an inference of Relational dimension

Similarly, the comparison of PC and LMD variables related to the perceptual variable indicated that when LMD had lower values (<30), the perceptual variable did not show a high numerical value (Figure 10). This was also observed in the comparative analysis of rules, especially in rules 5 and 21(n).

5. If (PC is VL) and (LMD is VH) then (Perceptual is M) (1)
21. If (PC is VH) and (LMD is VL) then (Perceptual is L) (1)

(n). Rules 5 and 8 21 to inference of Perceptual dimension

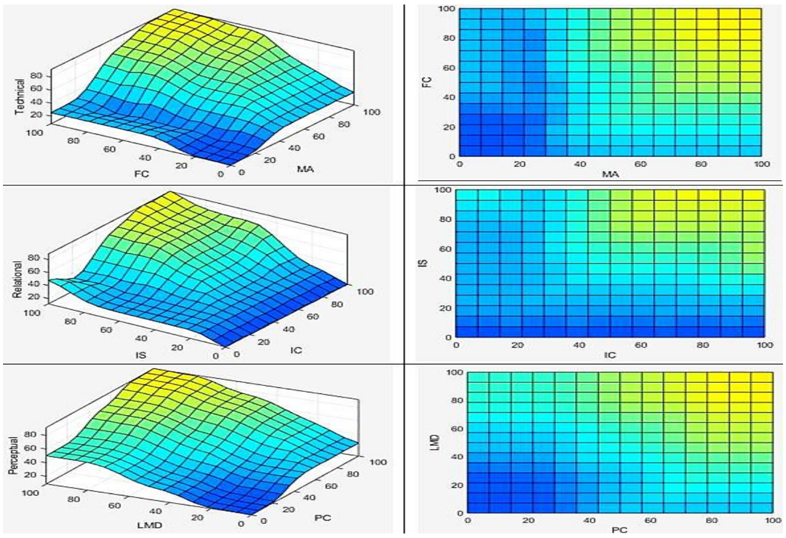

Figure 10. Surface plot of MA and IC related to Technical, IS, and IC related to Relational and LMD and PC related to Perceptual

Results in the third-level FIS

The outputs of the second level are considered as inputs at the third level, which includes technical, relational, and perceptual variables in which the output variable is the Competency of Mid-Level Nursing Managers (CMNM) as the main and final output (Figure 11). The effect of two input variables (technical and relational variables) on the CMNM output indicated that when the relational represented the lower values (< 50), even if the technical reported the higher values (>70), the CMNM did not show a high numerical value (Figure 12). The comparison of rules such as rules 23 and 102 also indicated this importance (o).

23. If (Technical is VL) and (Relational is VH) and (Perceptual is M) then (CMNM is M) (1)
102. If (Technical is VH) and (Relational is VL) and (Perceptual is M) then (CMNM is L) (1)

(o). Rules 23 and 102 to an inference of CMNM from comparing Technical and Relational dimensions

The comparison of technical and perceptual variables and their effect on the CMNM showed that in the low values of the perceptual variable (< 50), the CMNM did not display a high numerical value (Figure 12). In the comparison of rules 38, 86 and other rules (p), this relationship was also observable.

38. If (Technical is L) and (Relational is M) and (Perceptual is H) then (CMNM is H) (1)
86. If (Technical is H) and (Relational is M) and (Perceptual is L) then (CMNM is L) (1)

(p). Rules 38 and 86 to inference of CMNM from comparing Technical and Perceptual dimensions

In examining the effect of relational and perceptual variables on CMNM, the results showed that when the perceptual represented the lower values (<50) the

CMNM did not show a high numerical value (Figure 12), which was also observable in the comparative analysis of rules, especially in rules109 and 121(q).

109. If (Technical is VH) and (Relational is L) and (Perceptual is VH) then (CMNM is M) (1)
121. If (Technical is VH) and (Relational is VH) and (Perceptual is L) then (CMNM is L) (1)

(q). Rules 109 and 121 to inference of CMNM from comparing Relational and Perceptual dimensions

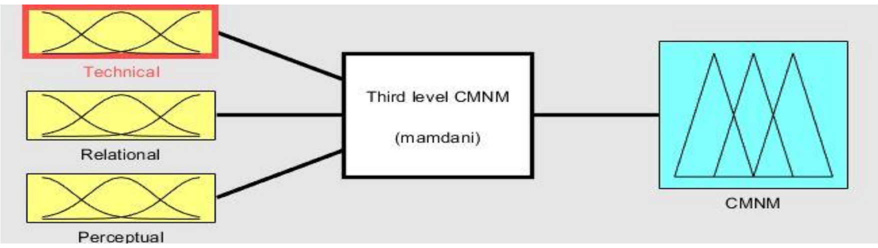

Figure 11. The input variables (Technical, Relational, Perceptual) and output variable (CMNM) variable in the third-level FIS

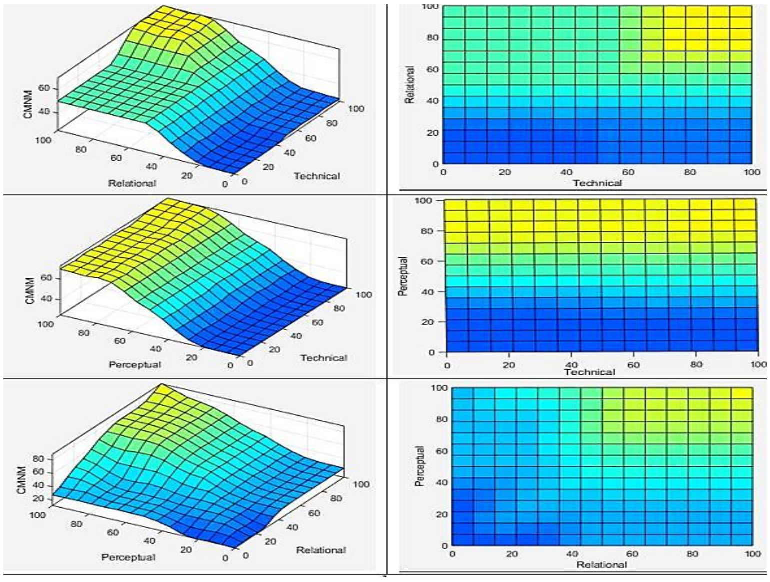

Figure 12. Surface plot of three variables Technical, Relational, and Perceptual related to CMNM.

Model validation

Model validation increases confidence in the model and its applicability. In the present study, validation of the model and its most important components wasaccomplished by limit and sensitivity analysis for all three FIS. In limit analysis, the FIS input values were changed in three limit states of very high (100), medium (50), and very low (0), and the model's sensitivity to these changes was examined. The model exhibited a logical behavior in response to limited input changes. For example, the logical behavior of the model at the third-level FIS input variables is shown in Table 1. For instance, in the very low state, it shifted towards zero (11/6), in the medium state it shifted towards 50, and in the very high state, it moved towards 100 (88.4), (Table. 1). The other two-level FIS input variables also exhibited the same logical behavior in response to limit input changes, indicating the validity of the model.

In sensitivity analysis, the output variable (CMNM) was measured by changing one of three variables (technical, perceptual, and relational) at the third FIS level (10%). We also found that perceptual competency had the greatest impact (57.4%) on the model output in comparison with the other two variables (Table 2).

Table 1. The limit analysis in the third-level FIS

Input			Output
Technical variable	Perceptual variable	Relational variable	Competency of mid-level nursing managers (CMNM)
0	0	0	11/6
50	50	50	50
100	100	100	88/4

Table 2. The sensitivity analysis in third-level FIS

Input			Output
Technical variable	Relational variable	Perceptual Variable	competency of middle nurse managers (CMNM)
50	50	60	57/4
50	60	50	50
60	50	50	50

Discussion

In this investigation, we used a three-level FIS based on experts' opinions to explain the competency of mid-level nursing managers/supervisors. The three-level FIS considers all situations by formulating rules for each level to evaluate competency and select managers, which improves accuracy.

In the previous study, the importance of all indicators, components, and dimensions of the present model was discussed and compared in different studies (38). Therefore, in this study, only the mutual effects of indicators and their prioritization at every level were discussed and compared based on the findings of the Fuzzy Inference System.

The first level of the FIS

The findings of this research indicated that managerial experience has a greater effect on management abilities than commitment to professional development. The reason for this can be understood by taking into account the concepts and sub-indices of managerial experience (time management, monitoring and evaluating performance, and information management), commitment to professional development, and lifelong learning (management knowledge, knowledge of employee development, professional ethics, skill in research, skill in calculation and distribution of human resources) as well as the target group in this study.

The mid-level candidates should have more desirable managerial experience and managerial experience should be prioritized considering the increasing exposure of mid-level nursing managers/supervisors to operational processes in hospitals. These managers would have a better understanding and control over hospital affairs and ultimately provide a better work environment for the organization.

Comparison of equipment and material assets management with budget planning knowledge, the findings revealed that equipment management may have a greater impact on financial competencies. Maintaining, monitoring, and storing equipment based on cost containment, as well as providing effective services and increasing productivity in hospitals (compared to budget knowledge) are expected from mid-level nursing managers/supervisors while budget planning knowledge is mainly pursued at the senior management level.

In this study, emotional intelligence (with sub-indices of conflict management, emotional resilience, trust building, and empowerment) had a greater impact on interpersonal competencies than personal and professional accountability. Since mid-level nursing managers/supervisors serve as the link between top-level/matrons and first-line nursing managers/ head nurses, they must possess self-awareness to manage their own emotions and empathy to understand the emotions of others. They should also develop interpersonal and social skills. This importance could be achievable through the desirable emotional intelligence in communication, which itself brings social obligations.

Comparing the presentation skill with the influence and impact on others showed that the influence and impact on others (with sub-indices of applying effective disciplinary strategies) could have a greater effect on the influencing skills. As the direct supervision of employees is done mainly by mid-level managers/supervisors, it is expected that mid-level managers possess highly developed skills in influencing and impacting others to create a constructive interaction with upstream and downstream levels and achieve the organizational goals. To eliminate anomalies in the working environment, create a calm environment for the employees, and promote quality improvement, mid-level nursing managers/supervisors are required to apply effective disciplinary strategies, which can be achieved through influencing others.

A comparison of organizational commitment (with sub-indices of inspiration and customer service-centeredness) and leadership and change management (with sub-indices of cultural intelligence) revealed a greater influence of organizational commitment on personal characteristics. In this respect, if nursing managers do not have sufficient motivation, interest, and commitment to providing services to patients, many valuable goals of the healthcare system will not be achieved. Committed managers stabilize leadership and create successful changes in the organization by staying in the organization.

In regards to the concept and sub-indices of self-confidence (creativity and innovation, initiative, risk-taking), the findings showed a greater impact of self-confidence on personal characteristics in comparison to leadership and change management. Managers can overcome the challenges and risks of the healthcare system by believing in their true abilities and skills. Mid-level managers/supervisors with low self-confidence cannot display favorable leadership and change management.

Likewise, critical thinking-based decision-making had a higher impact on personal characteristics than leadership and change management. The insufficient decision-making skills of managers will lead to various issues, and a deep understanding of problems can lead to the acceptance of new ideas and changes, further advancing the goals of the organization.

In the current study, organizational commitment and self-confidence had a relative influence on personal characteristics. However, in some rules, self-confidence had a greater influence on this variable compared to organizational commitment. Critical thinking-based decision-making also had a greater impact on personal characteristics in comparison to organizational commitment. This supports our previous findings regarding the importance of self-confidence and problem-solving skills for mid-level nursing managers/supervisors.

The second level of the FIS

The results also showed that management abilities had a greater impact on technical variables, which is justifiable according to the experts' opinions, considering the indicators corresponding to the management abilities compared to the financial competencies.

The comparison of interpersonal competencies with influencing skills showed a higher impact of influencing skills on the relational variable, which is also justified by the job description of mid-level nursing managers that involves supervising and training employees.

The comparison of personal characteristics and leading management development showed that the leading management development had a greater impact on the perceptual variable, which is in line with the experts' opinions, considering the indicators corresponding to the leading management development compared to the personal characteristics.

The third level of the FIS

The findings showed that the relational competencies had a greater impact on the mid-level nursing manager's competency compared to the technical competencies. The comparison of technical and perceptual competencies suggested that perceptual competencies have a greater impact on the mid-level nursing manager's competency. In addition, the current study revealed a greater influence of perceptual variables on the mid-level nursing manager's competency in comparison with relational variables.

Therefore, according to the experts' opinions, perceptual, relational, and technical competencies should have a higher priority in assessing the overall competency of mid-level nursing managers/supervisors, considering their corresponding indicators and components.

Regarding innovation in research, a review of published articles showed that so far, no national or international study has been found to investigate the nursing manager's succession planning, using the Fuzzy Inference System. We suggest future studies use other approaches based on multi-criteria decision-making methods to compare the findings of this study. About the limitations of this research, we should mention the results of this study are highly influenced by the opinions of nursing managers working in the hospitals affiliated with Tehran University of Medical Sciences, so care should be taken in generalizing its results to other universities of medical sciences with different ranks.

Conclusion

In the present study, a competency-based succession planning model for mid-level nursing managers/supervisors was presented to be used as a checklist/questionnaire to make strategies for choosing more competent mid-level managers. The continuous education and in-service training officials could help to enhance the effectiveness of training programs by organizing empowerment workshops along with allocating more time and resources to teach the priorities highlighted in the proposed model (e.g., managerial experience, equipment and material assets management, emotional intelligence, self-confidence, and strategic thinking). By employing an interdisciplinary approach, the FIS opens a new window to identify and compare competencies in the succession planning process for mid-level nursing managers/ supervisors.

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Conflicts of interest

The authors declare no conflict of interest in this study.

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