A Combined Multi-Criteria Decision-Making Framework for Process-Based Digitalisation Opportunity and Priority Assessment (DOPA)

Nihan Yıldırım, Istanbul Technical University, Turkey*
Birden Tuluğ Siyahi, Biligopex, Turkey
Oğuz Özbek, Biligopex, Turkey
İmran Ahioğlu, Istanbul Technical University, Turkey
Almira Selin Kahya, Technical University of Munich, Germany

ABSTRACT

With the introduction of Industry 4.0 and supporting technologies, both service and manufacturing companies faced external and internal pressure for “going digital.” In many cases, companies cannot decide on the digitalisation initiative due to preliminary groundwork to justify the required investment. For digitalisation priority setting under uncertain benefits, available digital technology selection methods lack the focus on process needs and do not fully utilise quality management tools in the multi-criteria decision-making (MCDM) framework. In this context, this study aims to propose a novel, context-independent, and process-based digital opportunity priority assessment (DOPA) methodology. The proposed approach utilizes critical to quality measures (CTQs), the causes with potential adversary effects as alternatives, and the importance, frequency, and digital control level of CTQs as the criteria in TOPSIS. AHP and Fuzzy AHP validate CTQ importance criteria. The study also presents a real industry application to validate the proposed model.

KEYWORDS

AHP, Digital Transformation, Digitalisation Roadmap, FAHP, FMEA, Industry 4.0, Priority Setting, Quality Management, Technology Selection, TOPSIS, Voice of Customer

INTRODUCTION

Digital transformation of enterprises, be it services or manufacturing-oriented, attracted importance and popularity in recent years. In an enormous scope, digital transformation provides tools and connectivity to enterprises to re-engineer their current processes, communication, and interactions and bring out opportunities to create better user experiences, new business models, and new revenue streams. Like other change-governing disciplines, a strategic and unified deployment
approach model would boost digitalisation success, create the best value for investment, provide a bridge between the technology providers and technology users, and finally catalyse the transition to a “digital future”. However, most small and medium-sized enterprises (SMEs) have not initiated the digital transformation due to the production and internal processes’ digitalisation challenges (Imgrund et al., 2018; Saam et al., 2016). The problem of capitalisation and technology identification/selection as a question of “How to identify the technology to adapt to which process?” has been on the agenda of researchers in recent years (Denner et al., 2018; Gimpel and Röglinger 2015; Hirt and Willmott 2014; HBRAS 2015).

Due to lack of the accumulated theoretical approaches and practices as cases or applications, today manufacturing organisations mostly tend or has to follow intuitive methods where the digitalisation ideas emerge from a black box, rather than analysing the actual needs of the organisation’s strategies and processes (Vanwersch et al. 2016; Zellner 2011; Vergidis et al. 2008). The manufacturing industry, especially SMEs, need tools and approaches to understand their process needs and design responses from digital transformation technologies and offerings. Current practices have rarely utilised the widely well-known and mature quality management and process improvement approaches to guide digitalisation strategies and actions. The importance of business process management for digital transformation is a growing research area (Stjepić et al., 2020).

In this context, this study aims to present a combined model that utilises quality management techniques (Voice of Customer, Process Risk Analysis) for selecting the process components that bear high operational risks and need improvement through digitalisation. In the MCDM adoption of Digital Opportunity Priority Assessment (DOPA) model, we adapted the TOPSIS method for ranking the causes of potential adversary effects. The methodology utilises the AHP and Fuzzy AHP (FAHP) techniques to validate the CTQ ranks for their importance in comparison to conventional expert scorings for CTQs. This way, we aimed to eliminate the redundancy and inconsistency of expert opinions. The findings underline the contribution of MCDM techniques to digitalisation decisions’ precision, consistency, and validity. A case study from the industry also presented an application for validating the model.

THEORETICAL BACKGROUND

Digital Transformation - Propositions, Benefits, Challenges

Previous studies such as Oesterreich and Teuteberg (2016), Erbay and Yıldırım (2018, 2019) discussed the linkages between production process needs and digital tools. They mostly concluded that the ROI or benefits of digitalisation primarily reside in process improvement and efficiency. Adaptability, resource efficiency, and the integration of supply and demand processes are the significant improvements enabled by the digital technologies of Industry 4.0 (Lu, 2017). Digital transformation also brings main functionalities to improve the KPIs, such as monitoring deviations (Bosch, 2015). KPMG (2016) listed the most common barriers against digitalisation efforts as; the lack of strategic vision, limited understanding of what “digitalisation” is, a poor understanding of impact (“can’t see ROI (Return on Investment)” syndrome), and not knowing where to start. Among those barriers, “where to start” still stands as a significant question especially for SMEs. From the survey of TUSIAD-BCG (2016), the top two obstacles against digital transformation from the customer perspective are high investment cost and the uncertainty in ROI, while low technological awareness and not-clarified ROI are the critical obstacles from the technology providers’ view. Like many other change initiatives, the lack of methodological tools providing comprehensive guidance disturbs digitalisation efforts from customer needs and expectations and creates an internal focus. Operational Process Dimension of Cap Gemini and MIT Building Blocks for Digital Transformation (2011) recall process analysis priority and improvement needs identification. Similarly, in the proposed transition plan to the digitalisation of ICT EU (2019), the first step is about “Connection for Operational Efficiency” which will create value in operational cost reduction.
Essential Quality Management and Process Improvement Methods Revisited

VoC (Voice of Customer) and CTQs (Critical to Quality) Measures in Process Improvement

In 6 Sigma, as a part of DMAIC, Voice of Customer (VoC) is the list of customer’s expectations, preferences, comments of a product or service in the discussion. It is the statement made by the customer on a particular product or service (Six Sigma Institute, 2019) where the need is transformed into requirements. VoC can be collected via interviews, surveys, focus groups and observations. Günaydın (2012) concluded that customer and satisfaction level voices should be considered to determine business strategies and define technical needs within six sigma critical success factors. Critical to Quality (CTQ) represents the parameters critical to the quality of the process or service to ensure the customer’s essential satisfaction; hence, CTQ problems can define quality improvement areas.

Process Risk Analysis

For understanding the process risks, their causes and effects, in literature, the most preferred technique is Failure Modes and Effect Analysis (FMEA). As a prospective risk analysis method (Asgari et al., 2017) FMEA is used to find the causes of the problem or a potential problem to improve the quality (Teixeira et al., 2012; Balaraju et al., 2019; Doshi, & Desai, 2017).

FMEA steps identify the failure modes, effects and the potential causes of failure, calculate the Risk Priority Number (RPN), and present corrective actions (Asgari et al., 2017). The RPN is a product of Severity, Occurrence, and Detection rankings on a 10 points scale (10 being the worst, 1 being the best score), prioritising the failure modes (Wessiani & Yoshio, 2018). The purpose of FMEA in a planned manufacturing process is to convert design characteristics into clearly defined operating conditions and guarantee that the outcomes and performance of the final product satisfy client demands and expectations (Chang et al., 2014; Tsai et al., 2016). Process FMEA focuses on identifying, analysing, and solving manufacturing processes problems (Mariajayaprakash, 2013).

Combining VoC/CTQ and FMEA for Quality Improvement

Levin et al. (2019) adapted FMEA and VoC in Risk Management Framework in Functional Activities for Cross-Functional Reliability. Kim et al. (2014) identified preventive measures for VoC management by analysing the causes and effects of factors contributing to high-risk service failure using FMEA through RPN assignment to each VoC data in the Service Failure Management field. Many researchers integrated the FMEA method with other process analysis and design methods. Aytaç (2011) combined the Fuzzy FMEA with Quality Function Deployment. Tsai (2017) adapted FMEA with Decision-Making Trial and Evaluation Laboratory (DEMATEL) to eliminate its failure in identifying the influence factors and the factors influenced. Wessiani and Yoshio (2018) proposed a combined methodology, including FMEA and Fault Tree Analysis in risk management. Liu (2016) combined FMEA with VIKOR, DEMATEL, and AHP for managing uncertainty in risk management of Processes. Geramian et al. (2019) also adopted a hybrid approach, including Fuzzy FMEA (FFMEA) and Collective Process Capability Analysis (CPCA) to modify and enhance quantitative features of FMEA. Tekez (2017) also applied Fuzzy TOPSIS to the FMEA model.

CHALLENGES OF PRIORITY SETTING FOR DIGITALIZATION: HOW CAN MULTI-CRITERIA DECISION MAKING BE COMBINED?

The Research Gap and Practice Need: Revisiting the Theoretical Background on Process Selection and Priority Setting for Digitalization

The problem of capitalisation on digitalisation (Denner et al., 2018; Gimpel and Röglinger, 2015; Hirt and Willmott, 2014) is challenging for organisations as many lack knowledge on digital technologies
to identify the technology-process fit (HBRAS 2015). Organisations mostly follow intuitive methods rather than analyse their actual needs regarding their strategies and process KPIs. Especially SMEs frequently fail to realise the implications of digitalisation for their operations fully and have difficulties in identifying an appropriate starting point for corresponding initiatives (Imgrund et al., 2018). Various process improvement methods focus on the activities before and after the improvement (Vanwersch et al. 2016; Vergidis et al. 2008), the actual progress and derivation of improvement ideas happen in a black box (Vanwersch et al. 2016; Zellner 2011; Roeglinger, Denner, and Püschel, 2017). Hence, despite mature knowledge, process improvement approaches have long-time been criticised for lack of guidance on putting process improvement into practice (Roeglinger, Denner, and Püschel, 2017; Adesola and Baines 2005). Although many enterprises encounter challenges in practice, research outputs does not provide practical recommendations to increase digitalisation feasibility (Imgrund et al., 2018). In response to this criticism, some researchers investigated how to structure the derivation of improvement ideas by compiling process enhancement patterns or redesign best practices (Mansar and Reijers 2007; Recker and Rosemann 2014). Kirchmer, Franz, and Gusain (2018) view the role of business process management within a digital transformation as a central one (Strepic et al., 2020). Other authors investigated the ways of prioritising the process improvement projects by multi-criteria decision analysis (MCDA) (e.g., Analytical Hierarchy Process) (Damani and Hanafizadeh 2013; Linhart et al. 2015; Mansar et al. 2009; Ohlsson et al. 2014; Vanwersch et al., 2016). Only a few studies combined process improvement approaches such as DMAIC with AHP (Fırat et al., 2017). Erbay and Yıldırım (2018; 2019) adopted QFD and AHP with mixed-integer programming to match the benefits of technologies and improvement needs with digital tools. Roeglinger, Denner, and Püschel (2017) proposed a method that supports organisations in exploiting the digitalisation potential of their processes by adopting action design research (ADR) and situational method engineering (SME). Imgrund and others (2018) recommended using Business Process Management (BPM) to define a set of capabilities for a management framework for process orientation to cope with digital transformation requirements.

In this context, process selection stands as the starting point of the digitalisation roadmap. Wiktorsson et al. (2018) mentioned that digitalising the previously less focused business processes, where IT integration level is less developed is a way to overcome the challenge of targeting and transforming processes. Digital innovation in companies requires reviewing all current processes to make the necessary changes to achieve the desired objectives (Nidp-Agbor, Cao, and Ehmann, 2018). It also involves analysing the maturity level of processes (Cevallos and Yoon, 2018).

MCDM models are widely adapted to digital technology selection problems in literature, including data enveloping, Analytical Network Process, AHP, Fuzzy AHP (FAHP), TOPSIS, QFD, PROMETHEE, MIP, simulation, etc. (Oztaysi, 2014; Mao et al., 2009; Lee, Cho, and Park, 2007; Lokesh and Jain, 2010; Sarkis and Talluri, 2004; Ngai and Chan, 2005; Farshidi et al., 2018; Becker et al., 2013; Majumder, 2015). In these studies, data collection has been chiefly based on expert views. There was significant growth in utilising MCDM techniques to solve technology decision problems (Hamzeh and Xu, 2019). However, almost all models focused on comparing and ranking the technologies based on the given criteria set, which involves evaluating the technology more than process needs or the improvement areas.

In practice and theory, risk-related quality management frameworks and MCDM methods have rarely been adapted for digitalisation priority setting upon process needs. For providing a roadmap to practitioners and to contribute to theory by validating the usability of quality management tools the research question of this study is structured below:

1. “How can process management and quality management methods be utilised in digitalisation priority assessment?”
2. “Can process risk-based view be embedded as criteria set in digitalisation decision-making models?”
3. “Does the digital priority of quality causes differ in conventional calculations and MCDM techniques?”
   a. “Does the ranking of causes from DPN scores vary by TOPSIS application and the conventional DPN calculation (as a product of CTQ importance, Cause Frequency and Cause Digital Control Level?”
   b. “Does the ranking of CTQs vary by conventional CTQ scoring and by weights from traditional AHP and Fuzzy AHP differ for the weights of CTQs?”

**METHODOLOGY – DECISION MODEL DESIGN FOR DIGITALIZATION OPPORTUNITY AND PRIORITY ASSESSMENT (DOPA)**

Within the proposed framework called DOPA, we combined (1) VoC-CTQ and (2) Process Risk Assessment methodology (inspired by FMEA) to identify and classify potential process problems. By doing so, the methodology prioritizes the causes of adversary effects in CTQ processes and matches them with digital solutions to provide basis for practical technology selection and road-mapping tool for organisations. By adapting the proposed methodology, the companies can understand their operational digitalisation priorities from process-based view.

**Model's Variables and Objective Function**

The objective of the function is minimisation for DOPA. The variables and equation are as follows:

\[
\text{CTQ} = \text{Critical to Quality (VoC)}
\]

Variable 1: \( \text{IMP}: \text{Importance} \) (Scale: 1: Very Low - 10: Very High)
Variable 2: \( \text{FREQ}: \text{Frequency} \) (Scale: 1: Very Rare - 10: Very Often)
Variable 3: \( \text{DCL}: \text{Digital Control Level} \) (Scale: 1: Very Low - 10: Very High)

Digitalization Priority Number = \( \text{IMP} \times \text{FREQ} \times \text{DCL} \) \hspace{1cm} (1)

\[
\text{OBJECTIVE FUNCTION} = \min\{\text{DPN}\} \hspace{1cm} \{\text{Max}=1000\}, \{\text{Min}=0\}
\]

Table 1 shows the variables and their theoretical roots with the data types to be utilised.

The process flowchart of the proposed DOPA Model is given in Figure 2 and explained below.

**Data Collection and Variable Measurement**

For model application, the data about the variables and their ratings or scores should be collected by site visits, interviews with process experts and consultants, and process observations. Experts score the variables in conventional DOPA application by the scales in Table 2.

For priority vector calculation of CTQ rankings in the AHP application, Saaty (1990) scales in Table 3 and for Fuzzy AHP the Fuzzy Linguistic Scales of Zhou and Lou (2012) in Table 4 will be used for rating the pairwise comparisons of CTQs.

**Multi-Criteria Decision Making (MCDM) Methods Adapated for Cause Priority Setting by DPN**

**Fuzzy AHP Technique**

Fuzzy AHP enables a precise practice in group decision-making by deriving priorities based on sets of pairwise comparisons (Kabir & Hasin, 2011). Wang and Chin (2011) defined Fuzzy AHP as a practical methodology for dealing with fuzziness and uncertainty in MCDM since fuzzy judgments are easier to provide than crisp judgments. Buckley (1985) introduced the geometric mean method...
to derive fuzzy weights from fuzzy pairwise comparison matrices. Csutora and Buckley (2001) and Wang and Chin (2006) used the eigenvector Lambda Max method in FAHP. As formula (2) presents, a triangular fuzzy number is denoted as:

\[ M = (l, m, u) \]

Its membership function:

\[ \mu_M(x) : \mathbb{R} \rightarrow [0, 1] \]

equals to:

\[ \mu_M(x) = \begin{cases} 
\frac{x - l}{m - l}, & x \in [l, m] \\
\frac{x - u}{m - u}, & x \in [m, u] \\
0, & otherwise 
\end{cases} \]

(2)
where \( l \leq m \leq u \), \( l \) and \( u \) stand for the lower and upper value of \( M \)’s support, respectively, \( m \) is the mid-value of \( M \) (Chang and Yang, 2011). Linguistic Fuzzy Scales perform the rating in Table 4 (Zhou and Lou, 2012). The steps of Chang’s extent analysis (1996) is extended by many researchers (Kabir and Hasin, 2011; Bozbura et al., 2007; Kahraman et al., 2004). Though it is conventional nature, AHP method is still popular in business analytics and many research applies it to contemporary business analytics problems, such as Sharma and Joshi (2020).

This study utilizes the Chang’s extent analysis for Fuzzy AHP application.

**TOPSIS Method and Application to Priority Setting by Causes of CTQ Effects**

The Technique of Ordered Preference by Similarity to Ideal Solution (TOPSIS) is among the widely used and primarily referred MCDM (Jozaghi et al., 2018) techniques in the literature (Sabaghi et al.,
### Table 2. Scales for IMP, FREQ, DCL Rating

| Frequency        | Rank    | Importance        | Rank    | Digital Control Level | Rank    |
|------------------|---------|-------------------|---------|-----------------------|---------|
| Very Often       | 8,9,10  | High              | H       | Almost no digital tech usage | 8,9,10  |
| Often            | 4,5,6,7 | Medium            | M       | Very few digitalization | 4,5,6,7 |
| Rarely           | 2,3     | Low               | L       | Significant digitalization | 2,3     |
| Almost None      | 1       | Very Low          | VL      | High digitalization    | 1       |

### Table 3. Fundamental Scale of Saaty (1990)

| Intensity of Performance on an absolute scale | Definition                                      |
|-----------------------------------------------|-------------------------------------------------|
| 1                                             | Equal importance                                |
| 3                                             | Moderate importance                             |
| 5                                             | Strong importance                               |
| 7                                             | Very strong or demonstrated importance          |
| 9                                             | Extreme importance                              |
| 2,4,6,8                                       | Intermediate values between two judgments        |

**Reciprocal values**

If activity i is assigned to one of the above numbers compared with activity j, then j gets the reciprocal value compared with activity j.

### Table 4. Fuzzy Linguistic scales and Triangular Fuzzy Numbers for Relative Importance of pairwise comparison (Zhou and Lou, 2012)

| Linguistic scales for importance | Triangular fuzzy numbers | Triangular fuzzy reciprocal numbers |
|----------------------------------|--------------------------|------------------------------------|
| Equally important (EI)           | (1,1,1)                  | (1,1,1)                            |
| Intermediate 1 (IM1)             | (1,2,3)                  | (1/3,1/2,1)                        |
| Moderately Important (MI)        | (2,3,4)                  | (1/4,1/3,1/2)                      |
| Intermediate Important (IM2)     | (3,4,5)                  | (1/5,1/4,1/3)                      |
| Important (I)                    | (4,5,6)                  | (1/6,1/5,1/4)                      |
| Intermediate 3 (IM3)             | (5,6,7)                  | (1/7,1/6,1/5)                      |
| Very Important (VI)              | (6,7,8)                  | (1/8,1/7,1/6)                      |
| Intermediate 4 (IM4)             | (7,8,9)                  | (1/9,1/8,1/7)                      |
| Absolutely Important (AI)        | (9,9,9)                  | (1/9,1/9,1/9)                      |
2015; Lai et al., 1994; Boran et al., 2009; Rostamzadeh et al., 2015; Shih, Shyur and Lee, 2011, Kukreja, Payyavula, Boehm and Padmanabhuni, 2013). Based on the vector space model of computation (Sabaghi et al., 2015), TOPSIS compares all decision alternatives of the problem. The method provides that the selected alternatives have not only the shortest distance from the positive ideal reference point (PIRP) but also the longest distance from the negative ideal reference point (NIRP) (Sabaghi, Mascle, and Baptiste, 2015; Hwang and Yoon, 1981). A set of alternatives is scored against criteria set on an absolute scale or a relative scale (Likert). The ideal theoretical alternative has the best score, and the theoretical non-ideal alternative has the worst score for each criterion (Kukreja et al., 2013). The criterion is scored using linguistic variables, as shown in Table 5 (Jadidi et al., 2008). The algorithm ranks the alternatives to minimise their vector distance from the ideal alternative ($S^+$) and maximise it from the non-ideal ($S^-$), giving the name to the technique as “Ordered Preference by Similarity to Ideal Solution”. (Kukreja et al., 2013). The steps of traditional TOPSIS are presented below (Hwang and Yoon, 1981):

**Step 1:** The normalisation of the decision-matrix: The formula (3) can be used to normalize:

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{m=1}^{m} (x_{ij})^2}} \quad (i = 1, \ldots, m; j = 1, \ldots, n)$$

**Step 2:** Calculation of the weighted normalised decision matrix: Per the formula (4), the normalised matrix is multiplied by the criteria weight:

$$V_{ij} = w_{ij} \cdot r_{ij} \quad (i = 1, \ldots, m; j = 1, \ldots, n)$$

**Step 3:** Determining the positive ideal and negative ideal solutions: The TOPSIS method aims to calculate the degree of distance of each alternative from positive and negative ideals. Therefore, in this step, the positive and negative ideal solutions are determined with the following formulas (5) to (6.2):

$$A^+ = \left( v_1^+, v_2^+, \ldots, v_n^+ \right)$$

$$A^- = \left( v_1^-, v_2^-, \ldots, v_n^- \right)$$

Table 5. The fundamental 1-9 Scale of Absolute Numbers (Source: Jadidi et al., 2008)

| Rating | Scale       |
|--------|-------------|
| 1      | Poor        |
| 3      | Medium Poor |
| 5      | Fair        |
| 7      | Medium Good |
| 9      | Good        |
so that:

$$v_j^+ = \left\{ \left( \max v_{ij} \mid j \in j_1 \right), \left( \min v_{ij} \left( x \right) \mid j \in j_2 \right) \right\} \quad i = 1, ..., m$$  \hspace{1cm} (6.1)

$$v_j^- = \left\{ \left( \min v_{ij} \mid j \in j_1 \right), \left( \max v_{ij} \left( x \right) \mid j \in j_2 \right) \right\} \quad i = 1, ..., m$$  \hspace{1cm} (6.2)

where \( j_1 \) and \( j_2 \) denote the negative and positive criteria, respectively.

**Step 4:** Calculating the distance from the positive and negative ideal solutions is enabled by (7.1), (7.2):

$$d_i^+ = \sqrt{\sum_{j=1}^{n} \left( v_{ij} - v_j^+ \right)^2}, \quad i = 1, ..., m; \quad j = 1, ..., n$$  \hspace{1cm} (7.1)

$$d_i^- = \sqrt{\sum_{j=1}^{n} \left( v_{ij} - v_j^- \right)^2}, \quad i = 1, ..., m; \quad j = 1, ..., n$$  \hspace{1cm} (7.2)

**Step 5:** Calculate the relative closeness degree of alternatives to the ideal solution: In this step, each alternative’s relative closeness degree to the ideal solution is obtained by formula (8):

$$C_i = \frac{d_i^-}{d_i^+ + d_i^-}, \quad i = 1, ..., m$$  \hspace{1cm} (8)
Case Study: Weighbridge Operation Digitalization Opportunity
Priority Setting by TOPSIS and Fuzzy AHP

For applying the extended version of DOPA with MCDM techniques as explained in the methodological process flow (Figure 1), we conducted a case study on a cement plant’s weighbridge operation. Based on the findings from the Hoshin Kanri practice on strategic objectives, the production process and weighbridge operation is selected for being priorly digitalized.

Step 1: The consultant team made observations in the plant and interviewed with managers/employees.
Step 2: “The material flow from quarries to the production process” is identified as critical.
Step 3: Focus process problem is identified as the weighbridge operation, which consists of two fundamental sub-processes: (1) Weighing the material coming from internal sources such as the quarry or the internal inventory, feeding the mill, and (2) Weighing the material coming from external suppliers to the mill.
Step 4: The CTQs are selected through Voice of Customer and Critical to Quality Analysis. The model showed that the digitalisation’s main target is decreasing the downtime and the errors in that weighbridge operation, which cause significant production time losses in the mill.
Step 5: Causes of Potential Adversary Effects of CTQs are explored by in-site observations and interviews with the company’s experts and employees. Next, by an inductive cause and effect analysis, the causes in Table 6 are listed.
Step 6: Process experts scored the Importance (IMP) of CTQs and Frequency (FREQ) of Causes in the process. The consultant scored the DCL by observing the process’s Current Digitalized Prevention and Current Digitalized Detection levels. If there exists no detection and prevention, then the DCL is 10.
Step 7: As-Is DPNs are calculated and ranked with using equation (1) (Table 6).
Step 8: The causes with the highest DPNs (constituting %50 or more than total DPNs) recommend a digitalisation action. Top-ranked causes with the highest DPNs (800) are analyzed by a Pareto analysis, as given in Figure 3.

Application of Analytic Hierarchy Process (AHP) for Weight Calculation of Each CTQ

The following steps are taken under the extended version of DOPA with MCDM techniques and are shown in Table 7. Three expert opinions with equal weights are collected for pairwise comparison of identified CTQ attributes, and weights of 0.4827, 0.2503, 0.1303, 0.0983, and 0.0384 are calculated respectively for each CTQ. The fundamental Scale of Saaty (Table 3) converted to Fuzzy Linguistic Scales (Table 4) for importance weights, then Consistency Index (CI) is calculated to show the consistency of the expert ratings and the reliability of FAHP weights.

Application of Fuzzy AHP for CTQ Weight Calculation

The fuzzy scale (Table 4) is applied to the AHP method in Table 8 to reduce the potential subjectivity from expert opinions based on the FAHP extent model of Chang and Yang (2011).

Sensitivity Analysis of Fuzzy AHP

Finally, a sensitivity analysis is conducted to observe the tolerance limits of the importance of weights. Best-worst method Sensitivity Analysis of FAHP calculations are performed by adding a new alternative as Datum to the CTQ alternatives, and then by testing the alternative pairwise comparison including this Datum, showing the sensitivity limits of the rankings (Yükselkylıdz et al., 2018; Özdağoğlu, 2008). For sensitivity analysis, the new alternative’s (Datum) Pairwise comparison matrix values are the minimum values in pairwise comparison tables of other alternatives (CTQs) in the Best Case scenarios (Table 9).
On the other hand, in the Worst Case scenario (Table 10), the maximum values in pairwise comparison tables of other alternatives (other CTQs) are taken as the Datum alternative’s pairwise comparison values. The worst-case scenario assumes that the new alternative has higher importance than the other CTQs. In contrast, the best case scenario assumes that all other alternatives have higher significance than the fresh alternative. Interval of the “importance” values in case of the addition of the latest alternative, remained the same (Ozdagloğlu, 2008). The results indicated that adding a new CTQ (alternative) did not alter the ranking or priorities of five CTQ indicators and did not change the decision-making attitude.

| Identified CTQ | Potential CTQ Adversary | Identified Causes | Assessors | Assessors | Currently Digitalized |
|---------------|-------------------------|-------------------|-----------|-----------|----------------------|
|               |                         |                   | 1         | 2         | 3                    | 1        | 2        | 3        | Prevalence | DCL | DPN (AS-IS) | % of DPN in Total DPN | DPN Cumulative Sum% | RANK |
| Continuous weighbridge operation | Incorrect weighting Productivity losses Mill downtime | Shift change interruption | 10 | 10 | 10 | - | - | 10 | 800 | 8.78% | 8.78% | 1 |
| Correct reporting | Error at costing, pricing and payments Discrepancy with 3rd party tally Regulatory penalties (MAPEG) | Wrong origin recorded | 10 | 10 | 9 | - | - | 10 | 800 | 8.78% | 46.25% | 1 |
| Contract enforcement | Over purchase Excess inventory Production interruption | Weighbridge data is not automatically fed into the ERP | 10 | 10 | 10 | - | - | 10 | 700 | 7.68% | 82.01% | 7 |
| Optimal inventory retention | Over time control Increased cost of operations | Overtime due to annual leave coverage | 6 | 6 | 5 | - | - | 10 | 360 | 3.95% | 94.73% | 12 |
| Overtime control | | Overtime due to downtime in normal working hours | 6 | 7 | 7 | - | - | 10 | 360 | 3.95% | 98.68% | 12 |
| | | Absenteeism | 2 | 3 | 3 | - | - | 10 | 120 | 1.32% | 100.00% | 17 |

Table 6. Digital Opportunity and Priority Assessment of CTQs
Comparison of CTQ Importance Ratings in Conventional DOPA and From AHP Analyses

The rankings differed when CTQ Importance ratings from conventional DOPA and Table 11 compares the AHP Weight calculations from two methods (Table 11). Though the DPN results provide evidence for the priority of Causes related to CTQ 1, Continuous operation of Weighbridge, from the importance scorings, this CTQ remains the 3rd important CTQ. In contrast, AHP and FAHP results provide ultimate weight (almost two times of CTQ 1 weight) to CTQ1. Hence, the experts score the importance once again.

| Eigenvector | 0.4827 | 0.2503 | 0.1303 | 0.0983 | 0.0384 |
|-------------|--------|--------|--------|--------|--------|
| Continuous Operation of Weighbridge | 0.53 | 0.62 | 0.49 | 0.48 | 0.28 |
| Correct Weighting and Reporting | 0.18 | 0.21 | 0.30 | 0.29 | 0.28 |
| Matching Contract - Order - Purchase Enforcement | 0.11 | 0.07 | 0.10 | 0.10 | 0.28 |
| Maintain Optimal Material Inventory | 0.11 | 0.07 | 0.10 | 0.10 | 0.12 |
| Overtime Control | 0.08 | 0.03 | 0.01 | 0.03 | 0.04 |

Table 7. AHP for Weight Calculation of CTQs

| CTQ Matrix | Continuous Operation | Correct Weighting and Reporting | Matching Contract – Order/Purchase Enforcement | Maintain Optimal Material Inventory | Overtime Control |
|------------|----------------------|---------------------------------|---------------------------------------------|-----------------------------------|----------------|
| Continuous Operation of Weighbridge | 1 | 3 | 5 | 5 | 7 |
| Correct Weighting and Reporting | 0.33 | 1 | 3 | 3 | 7 |
| Matching Contract - Order - Purchase Enforcement | 0.20 | 0.33 | 1 | 1 | 7 |
| Maintain Optimal Material Inventory | 0.20 | 0.33 | 1,00 | 1 | 3 |
| Overtime Control | 0.14 | 0.14 | 0.14 | 0.33 | 1 |
| Total | 1,876 | 4,809 | 10,142 | 10,333 | 25,000 |

Table 8. Fuzzy AHP for Weight Calculation

| CTQs | Continuous Operation | Correct Weighting and Reporting | Matching Contract – Order/Purchase Enforcement | Maintain Optimal Material Inventory | Overtime Control |
|------|----------------------|---------------------------------|---------------------------------------------|-----------------------------------|----------------|
| 1) Continuous Operation of Weighbridge | 1 | 1 | 1 | 2 | 3 | 4 | 4 | 5 | 6 | 4 | 5 | 6 | 6 | 7 | 8 |
| 2) Correct Weighting Reporting | 0.25 | 0.33 | 0.50 | 1 | 1 | 1 | 2 | 3 | 4 | 2 | 3 | 4 | 6 | 7 | 8 |
| 3) Matching Contract - Order - Purchase Enforcement | 0.17 | 0.20 | 0.25 | 0.25 | 0 | 0.5 | 1 | 1 | 1 | 1 | 1 | 1 | 6 | 7 | 8 |
| 4) Maintain Optimal Material Inventory | 0.17 | 0.20 | 0.25 | 0.25 | 0 | 0.5 | 1 | 1 | 1 | 1 | 1 | 1 | 2 | 3 | 4 |
| 5) Overtime Control | 0.13 | 0.14 | 0.17 | 0.13 | 0.14 | 0.17 | 0.13 | 0.14 | 0.17 | 0.25 | 0.33 | 0.50 | 1 | 1 | 1 |
Application of TOPSIS for Causes Priority Setting and Comparison With DPN Ranking From Conventional DOPA

Traditional TOPSIS is applied to the decision matrix of identified causes created by expert ratings in the DOPA template by utilising equation (1) and TOPSIS model given in equations (3)-(8) in Table 12. In DPN ranking from DOPA, the model selected the most important causes to be improved (“Shift change interruption”, “Misc personnel-related downtime”, “Wrong origin recorded”, “the wrong destination recorded” and “WB data is not automatically fed into ERP”). However, TOPSIS results revealed that the top-ranked causes are “WB data is not automatically fed into ERP” from CTQ 5 and “The wrong origin recorded”, “the wrong destination recorded” “the wrong query recorded” from CTQ 2; hence they have to be digitised. “Shift change interruption” and “Miscellaneous personnel-related downtime” causes are also in the first six causes ranked in TOPSIS; however, their priority has changed. According to these findings, the ideal solution distance reflected in TOPSIS was not elaborated in conventional DPN calculation and rating. Utilising two different methods provided a multi-perspective approach to the problem and recall for iterating the evaluation of variables by experts consistently.

DISCUSSION

The difference between DPN calculations and AHP findings is also aligned with the literature on FMEA, which inspired the DPN calculation of our model. Traditionally, FMEA addresses problems (“causes” in the DOPA model) in order from the largest RPN to the smallest ones (Xiao et al., 2011).
As stated by the same authors, in the FMEA method, three factors (Severity (S), Occurrence (O), Detection (D)) have different weights in the system, moderate weights for factors S, O are higher than the weight of D for some non-repairable systems. When this rule is reflected in our DOPA model’s DPN calculation through the Importance of CTQs, Frequency and Digital Control Level of Causes, the decision-maker should better utilize the weights provided from AHP in calculating the final DPN of causes. Though FMEA has several weaknesses (Xu et al., 2002; Gargama and Chaturvedi, 2011; Liu and Liu, 2013; Mandal and Maiti, 2014), the MCDM methods can help enhance FMEA and other process risk analysis tools. However, these have not been comparatively discussed and combined to validate failure and effect analyses (Tekez 2017; Lolli et al., 2015). The proposed model presents a combined approach of FMEA and MCDM methods for a more robust interpretation of FMEA Figure 4 presents an overall comparison of FMEA with DOPA.

| CTQs | CTQ1 | CTQ2 | CTQ3 | CTQ4 | CTQ5 | DATUM |
|------|------|------|------|------|------|-------|
| 1    | 2    | 1    | 1    | 1    | 1    | 1,12  |
| 0,25 | 0,33 | 0,50 | 0    | 0    | 0    | 0,13  |
| 0,17 | 0,20 | 0,25 | 0,25 | 0,25 | 0,25 | 0,13  |
| 0,17 | 0,20 | 0,25 | 0,25 | 0,25 | 0,25 | 0,13  |
| 0,13 | 0,14 | 0,17 | 0,13 | 0,14 | 0,17 | 0,13  |
| 0,13 | 0,14 | 0,17 | 0,13 | 0,14 | 0,17 | 0,13  |

Table 10. Worst Case Sensitivity Analysis of FAHP calculation on CTQ Weights by Datum

| CTQs | Geometric Mean | Fuzzy Weight | Average | Normalized Weights | RANK |
|------|----------------|--------------|---------|--------------------|------|
| CTQ 1 | 3,238           | 3,928        | 4,579   | 0,299              | 0,430 | 0,605 | 0,445 | 0,426 | 1     |
| CTQ 2 | 1,817           | 2,297        | 2,828   | 0,168              | 0,252 | 0,374 | 0,264 | 0,253 | 2     |
| CTQ 3 | 1,070           | 1,218        | 1,414   | 0,099              | 0,133 | 0,187 | 0,140 | 0,134 | 3     |
| CTQ 4 | 0,891           | 1,058        | 1,260   | 0,082              | 0,116 | 0,166 | 0,12  | 0,11  | 4     |
| CTQ 5 | 0,378           | 0,435        | 0,514   | 0,035              | 0,048 | 0,068 | 0,05  | 0,04  | 5     |
| DATUM | 0,177           | 0,198        | 0,225   | 0,016              | 0,022 | 0,030 | 0,02  | 0,02  |       |

Table 11. Comparison of CTQ Importance Ratings in Conventional DOPA and AHP Analyses (*Average Scorings (1-8) of Experts for CTQs Importances in Conventional DOPA)

| CTQs | AHP | FAHP | Difference |
|------|-----|------|------------|
| 1    | 0,483 | 0,461 | -0,022 |
| 2    | 0,250 | 0,239 | -0,011 |
| 3    | 0,130 | 0,124 | -0,006 |
| 4    | 0,098 | 0,094 | -0,004 |
| 5    | 0,038 | 0,037 | -0,002 |

As stated by the same authors, in the FMEA method, three factors (Severity (S), Occurrence (O), Detection (D)) have different weights in the system, moderate weights for factors S, O are higher than the weight of D for some non-repairable systems. When this rule is reflected in our DOPA model’s DPN calculation through the Importance of CTQs, Frequency and Digital Control Level of Causes, the decision-maker should better utilize the weights provided from AHP in calculating the final DPN of causes. Though FMEA has several weaknesses (Xu et al., 2002; Gargama and Chaturvedi, 2011; Liu and Liu, 2013; Mandal and Maiti, 2014), the MCDM methods can help enhance FMEA and other process risk analysis tools. However, these have not been comparatively discussed and combined to validate failure and effect analyses (Tekez 2017; Lolli et al., 2015). The proposed model presents a combined approach of FMEA and MCDM methods for a more robust interpretation of FMEA Figure 4 presents an overall comparison of FMEA with DOPA.
CONCLUSION

By combining FMEA and VoC methods for digitalization priority setting problems, the suggested method provides a contextual template to identify, prioritise, and select critical quality parameters, causes, and adversary effects that offer digitalisation opportunities actionable items and benefits insight in a holistic approach. The suggested methodology takes its roots in process management and improvement tools, interpreting and using them in the context of “digitalisation”. For policy and managerial implications, the study also contributes to the methodological knowledge base on “how to identify the technology to adapt to which process” which has been on the agenda of researchers in recent years (Denner et al., 2018; Gimpel and Röglinger, 2015; Hirt and Willmott, 2014; HBRAS, 2015).

Table 12. Traditional TOPSIS Application for on the top causes of Potential Adversaries

| CTQs | Identified CTQ | Potential Adversary | CTQ Weight | Identified Causes | Weighted Evaluation | Normalized Matrix | S+ | S- | CI |
|------|---------------|---------------------|------------|------------------|---------------------|------------------|-----|-----|----|
|      |               | Incorrect weighing  | 0.46 1     | Shift change     | 3.38 4.61 4.61     | 0.34 0.47 0.35   | 0.01 | 0.20 | 0.97 |
|      |               | Production losses   | 0.46 1     | Misc personnel   | 3.38 4.61 4.61     | 0.34 0.47 0.35   | 0.01 | 0.20 | 0.97 |
|      |               | Mill downtime       | 0.46 1     | Lunch break      | 3.38 3.84 4.61     | 0.34 0.39 0.35   | 0.01 | 0.17 | 0.95 |
|      |               | Cleaning downtime   | 0.46 1     | Cleaning         | 3.38 3.23 4.61     | 0.34 0.33 0.35   | 0.02 | 0.15 | 0.90 |
|      |               | Weightbridge        | 0.46 6     | Weightbridge     | 3.38 2.30 4.61     | 0.34 0.23 0.54   | 0.03 | 0.16 | 0.85 |
|      |               | Out of calibration  | 0.46 7     | Out of calibration| 3.38 1.38 4.15    | 0.34 0.14 0.42   | 0.06 | 0.13 | 0.70 |
| 1    | Continuous    | Weighbridge         | 0.24 17    | Wrong origin     | 1.91 2.31 2.39     | 0.19 0.23 0.24   | 0.06 | 0.20 | 0.48 |
|      |               | operation           | 0.24 18    | Wrong destination| 1.91 2.31 2.39     | 0.19 0.23 0.24   | 0.06 | 0.20 | 0.48 |
|      |               | Error at costing    | 0.24 14    | Wrong quary       | 1.91 2.15 2.39     | 0.19 0.22 0.24   | 0.07 | 0.16 | 0.45 |
|      |               | Discrepancy         | 0.24 11    | Wrong material    | 1.91 1.43 2.39     | 0.19 0.14 0.24   | 0.09 | 0.04 | 0.33 |
|      |               | Regulatory penalties| 0.24 12    | Wrong provider    | 1.91 0.64 2.39     | 0.19 0.06 0.24   | 0.12 | 0.04 | 0.23 |
|      |               | Regulatory penalties| 0.24 13    | Wrong vehicle     | 1.91 0.56 2.39     | 0.19 0.06 0.24   | 0.12 | 0.04 | 0.22 |
|      |               | Reciept             | 0.24 15    | Wrong weight      | 1.91 0.32 2.39     | 0.19 0.03 0.24   | 0.13 | 0.03 | 0.21 |
|      |               | Recorded            | 0.24 16    | Wrong tare        | 1.91 0.32 2.39     | 0.19 0.03 0.24   | 0.13 | 0.03 | 0.21 |
| 2    | Correct       | Reporting           | 0.04 9     | Absenteesim       | 0.27 0.10 0.57     | 0.03 0.01 0.04   | 0.25 | 0.00 | 0.00 |
|      |               | Increased cost      | 0.04 10    | Overtime due to   | 0.27 0.24 0.57     | 0.03 0.02 0.04   | 0.24 | 0.00 | 0.00 |
|      |               | operations          | 30.04 8    | Overtime due to   | 0.27 0.21 0.57     | 0.03 0.02 0.04   | 0.24 | 0.00 | 0.00 |
|      | Overtime      | control             |            |                  |                     |                  |      |      |     |
| 3    | Overtime      | Control             | 0.12 19    | Over purchase     | 0.91 1.24 1.24     | 0.09 0.12 0.12   | 0.15 | 0.01 | 0.08 |
|      | enforcement   | Excessive           |            | Weightbridge data | 0.72 0.94 0.94     | 0.07 0.09 0.09   | 0.17 | 0.01 | 0.03 |
|      |              | inventory           |            | is not automatically fed into the ERP | 0.72 0.94 0.94 | 0.07 0.09 0.09 | 0.17 0.01 0.03 |
|      |              | Production          |            |                  |                     |                  |      |      |     |
|      |              | interruption        |            |                  |                     |                  |      |      |     |

9.97 9.78 13.1 A+ 0.34 0.47 0.46

A- 0.03 0.01 0.04
For the uniqueness of the method, risk analysis and the prioritisation of the causes occur as the innovative components of the proposed model by reflecting failure and effect dimensions of the processes in a product of (DPN) importance, frequency, and digital control level variables. In digitalization roadmapping, rather than choosing a process, identification of the critical quality defects and their causes can better reflect the technology utilisation needs. Because it can build solid
linkages with digital action via cause detection and prevention measures. The interface of DOPA and digital technologies is the digital control level (DCL) as a variable that allows the digital technology to intervene in the process’s digital control mechanisms. In expert scorings of criteria in MCDM (as used in TOPSIS in this study) can be criticised for embedding bias and inconsistency. For minimizing the subjectivity, the study also used the Fuzzy AHP approach for finding the weights of CTQs in addition to the Importance ratings in TOPSIS. By testing the consistency and sensitivity of these AHP weights, the results are validated. As a validity control mechanism, comparing the CTQ Importance rankings from TOPSIS rating and FAHP weights provides the model’s robustness. Otherwise, the TOPSIS ranking of the causes, on its own, would remain naïve and would not be fully utilising the functionality of the MCDM approach. Moreover, adapting the fuzzy approach removes the risk of subjectivity to a considerable level. The case study revealed that the digital priority-setting approach is adaptable to manufacturing processes by using critical to quality parameters, the causes of their adversary effects as alternatives to be evaluated in the production system.

Another significant finding from the case study is that the ranking of CTQs by AHP and Fuzzy AHP weights did not change. However, the CTQ importance rankings from both AHP applications differed from the ranks of CTQs from the direct scoring of experts in the conventional DOPA framework. The TOPSIS application also provided different results (levels of causes) from traditional variable and DPN calculation scoring. The combination of two different methods provided a multi-perspective approach to the problem and recall for iterating the evaluation of variables by experts consistently. Hence, the proposed methodology can provide insights to practitioners that MCDM methods can work efficiently in process and risk analyses to remove the subjectivity and inconsistency of expert ratings.

This research’s limitations are the equal-weighted application of digital priority setting functions’ variables (Frequency, Importance, and DCL). The equal weights can be adjusted per the strategic approaches and needs of the practitioners. For doing so, to overcome the critics of Olson (1994) for equal-weighted TOPSIS application, Further research can also adapt other MCDM methods such as DEMATEL for relative weights of criteria. To achieve a complementary and holistic view, future studies can focus on practical applications of the suggested method and associating digitalisation options with the ranked causes of adversary effects by applying multi-criteria decision-making methods of AHP, TOPSIS, Quality Function Deployment (QFD).

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