# Fuzzy Set Qualitative Comparative Analysis as a Tool for Indivudual and Organizational Decision Support in Technology Adoption: Revealing the Potential

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As the digital economy and society rapidly grow, individual and organizational adaptation to technology has gained substantial concern across various sectors. However, this process involves many challenges, including uncertainty and complexity arising from factors such as the reliability, feasibility, and compatibility of technologies. Based on evidence from existing literature, this study proposes applying the fuzzy set qualitative comparative analysis (fsQCA) approach as a valuable tool in investigating associated challenges and complex configurations of influential factors within the context of individual and organizational technology decision-making in technology adoption. The fsQCA has emerged as a popular tool in qualitative analysis, particularly in recent years, where its use has grown substantially. This paper conducts a systematic literature review of journal articles published between 2015 and 2023 using fsQCA, focusing on digital transformation, AI, IoT, e- and m-commerce applications, digital assistants, business analytics, sustainable development, and machine learning. This study offers a detailed review of related research, the implications of the identified trends, and the potential for future research utilizing fsQCA to explore performance and human behavior in technology adoption and organizational technology decision-making contexts.

**Keywords:** consumer behavior, decision analytics, fsQCA, literature review, technology adoption

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## 1 Introduction

Today's fast-changing digital world has increased interest in using artificial intelligence (AI) and innovative technological tools across various sectors. However, this surge in technological interest has also introduced numerous challenges that make the decision-making process complex, particularly regarding how individuals and organizations interact with and adopt these new technologies. At the individual level, a person's decisions and actions are key to their intentions to adopt and persist with a specific system or technology (Granić, 2023). At the organizational level, the emergence of advanced technologies, for example, AI, big data analytics, and Internet of Things (IoT) has enabled organizations to automate and optimize their process and improve innovation capabilities (Fan et al., 2023; Costa-Climent et al., 2023). However, the successful implementation of new technology depends not solely on the technology itself but on how well it aligns with other factors (e.g., behavior of employees, top management support) within the organization and society (Haber & Carmeli, 2023). These emphasize the importance of understanding complex relationships between consumer preferences and perceptions related to technology products and services, as well as examining how organizations navigate the complexities of technology adoption and integration into their operations. This is where fuzzy-set qualitative comparative analysis (fsQCA) can be valuable. fsQCA (Ragin, 2000) is a methodology that allows researchers to analyze how different combinations of variables (i.e., causal relationships) contribute to specific outcomes (Hew et al., 2023; Chen & Ye, 2023), even in the presence of uncertainty.

fsQCA has emerged as a promising method for handling the complexities inherent in individual and organizational decision-making contexts. By combining qualitative and quantitative elements, fsQCA offers a holistic approach (Ragin, 2008) to analyzing complex data sets and identifying key drivers of desired outcomes. fsQCA involves a systematic process of identifying and representing the key variables in a research problem and supports identifying the causal relationships among the variables. This approach allows researchers to examine the causal relationships among variables more holistically than traditional regression or correlation analysis (Kraus et al., 2018; Pappas & Woodside, 2021), which assumes linear relationships between variables and does not account for non-linear or interactive effects. Due to its potential and ability to handle complex data, fsQCA has been applied in various research contexts (Kraus et al., 2018), including consumer behavior studies (Diwanji, 2023), organizational decision-making (e.g., Fiss, 2011; Kumbure et al., 2020), information systems and marketing (Pappas & Woodside, 2021), education (e.g., Plewa et al., 2016), and online business (e.g., Pappas et al., 2016), to mention a few. As such, it has become an increasingly crucial methodological tool for researchers seeking an in-depth understanding of complex social phenomena (Kumar et al., 2022).

The primary goal of this review study is to explore the application of fsQCA as a valuable tool for investigating the key factors and configurations that impact individual and organizational decision-making when considering the adoption of technology. Focusing on insights from various domains such as digitalization, big data analytics, visual analytics, machine learning, explainable AI, business analytics, Internet of Things (IoT), knowledge collaboration, information systems, and sustainability development, this paper seeks to reveal the applicability and effectiveness of fsQCA across a wide range of consumer behavior and organizational contexts. Accordingly, the primary research question for this systematic literature review is set as follows: What is the current state of fsQCA research in emerging technology, specifically in consumer behavior with technology adoption and organizational technology decision-making? Consumer behavior and technology adoption research focuses on understanding how individuals interact with and adopt new technologies. It examines factors influencing consumers' decisions to accept or reject technology and their usage patterns and attitudes toward technology products or services. In contrast, organization technology decision-making research investigates how organizations make decisions regarding the adoption, implementation, and management of technology. It analyzes the organizational processes, structures, and dynamics that influence technology adoption, such as decision-making frameworks, resource allocation, and organizational culture. Both research areas aim to provide insights into the complex interactions between individuals, organizations, and technology, helping offer strategies for successful technology adoption and implementation. With this research question, we focus on fsQCA research to deliver valuable insights regarding the influences of various factors and their connections to behavior intentions and organizational decision-making processes.

Several review studies have already addressed fsQCA research across various domains, particularly in business and management (Wagemann et al., 2016), entrepreneurship and innovation (Kraus et al., 2018), and bibliometric analysis in business and consumer research (Kumar et al., 2022; Diwanji, 2023). However, our review paper distinguishes itself from existing reviews by focusing specifically on using fsQCA in the context of technology adoption at the individual and organizational levels. By revealing insights into fsQCA's application and efficacy within this context, we aim to bridge the gap in understanding the utilization of fsQCA in research on the digital era through a detailed review of relevant studies.

## 2 Fuzzy-set qualitative comparative analysis (fsQCA)

Qualitative comparative analysis (QCA) is a set-theoretic methodology (Chuah et al., 2021) used to analyze the relationships between conditions and outcomes.

fsQCA is a variant of QCA, introduced by Ragin (2000, 2008), based on fuzzy set theory (Zadeh, 1965), which examines the complex relationships between causal conditions and outcomes while dealing with associated relationship uncertainties.

A fuzzy set is defined on a non-empty set (universal set) $U$ by a mapping $\mu_A\colon U \to [0,1]$, where $\mu_A$ is called a membership function of $A$. For any $x \in U$, the value $\mu_A(x) = A(x)$ is called a degree of membership of $x$ to fuzzy set $A$. In fsQCA, we use evidence from cases and theoretical knowledge to calibrate the states of variables represented by fuzzy sets. The approach relies on two key concepts, consistency and coverage, to assess causal relationships between variables (Chuah et al., 2021), specifically the relationship $A \Longrightarrow B$, depending on available data. Consistency measures the extent to which the data supports the investigated claim, $A \subseteq B$, by examining the proportion of cases where $A$ coincides with $B$ among all cases where $A$ occurs in the data (Ragin, 2008; Kumbure et al., 2022a). A low consistency score for a given causal configuration indicates weak empirical evidence to support its existence. Coverage, on the other hand, indicates how much of the outcome variable $B$ is explained by $A$ (Ragin, 2008; Kumbure et al., 2022a). It measures the proportion of cases in which $B$ is present among those cases where $A$ is present (Ragin, 2008). A high coverage score suggests that $A$ is an important factor in explaining the occurrence of $B$. The fsQCA is primarily based on these two concepts - their definitions can be presented according to Kumbure et al. (2022a) as follows:

$$Consistency(A \Longrightarrow B) = \frac{Card\ (A \cap B)}{Card(A)} = \frac{\sum_{i=1}^{n} \min\ (A(x_i), B(x_i))}{\sum_{i=1}^{n} A(x_i)} \tag{1}$$

$$Coverage(A \Longrightarrow B) \quad = \frac{Card\ (A \cap B)}{Card(B)} = \frac{\sum_{i=1}^{n} \min\ (A(x_i), B(x_i))}{\sum_{i=1}^{n} B(x_i)} \tag{2}$$

Where $A$ and $B$ are fuzzy sets on a universal set $U = \{x_1, x_2, \ldots, x_n\}$. Here, we assume that $Card\ (A) \neq 0$ and $Card\ (B) \neq 0$ with respect to the relationship $A \Longrightarrow B$. When $A \subseteq B$ (i.e., $A \cap B = A$), the consistency is 1(ideal consistency), indicating that $A$ almost always leads to $B$ ($B$ is fully consistent with $A$). Besides, the coverage = 1 expresses that only $A$ is connected with the outcome $B$ in the data ($B \subseteq A$). If some other conditions affect $B$, the coverage value would be lower than 1.

Overall, we seek to achieve a balanced combination of consistency and coverage for a particular situation to ensure the theoretical and empirical robustness of the outcomes (Kumbure et al., 2022a). When a relationship has very high consistency but low coverage, it fails to describe many cases, suggesting a potentially weak relationship. Contrarily, when a relationship has very high coverage but low consistency, it also signifies a weak relationship due to insufficient evidence from the data (Elliot, 2013).

## 3 Methodology

The systematic review presented in this study attempted to identify the applications of fsQCA approaches in research in decision support and adoption of new technology. The methodology followed in this systematic literature review was based on the review protocols and guidelines introduced by Kichenham (2004) and Synder (2019) and techniques demonstrated by Kumbure et al. (2022b). The steps of the review methodology are discussed in detail next.

### 3.1 Search strategy

To identify relevant studies for this systematic literature review, we performed an automated search using the Web of Science (WoS) database, which is a widely utilized database (Shukla et al., 2019) that provides access to a vast collection of scholarly literature across various disciplines. To generate the search strategy, we used keywords "fuzzy set qualitative comparative analysis," "fsQCA," "fuzzy set-QCA," "fuzzy-set QCA," and application-related keywords, "artificial intelligence," "AI," "internet of things," "IoT," "digitalization," "explainable AI," "machine learning," "deep learning," "big data," "visualization," "business analytics," "sustainable development," and "knowledge collaboration." The search string was finalized using these keywords, which yielded a set of relevant studies. Articles were searched using the search string in the titles and abstracts.

### 3.2 Inclusion & exclusion criteria and study selection

The inclusion and exclusion criteria were applied as follows: only journal articles were considered, while conference papers and book chapters were excluded. This is because journal articles typically undergo a rigorous peer review and focus on in-depth analysis and discussion, ensuring the quality and reliability of research. Articles had to be written in English and published between 2015 and 2023. In the next stage, journal articles with full-text availability were considered, and finally, relevant papers were selected by scanning abstracts. This selection process focused on topics such as AI, machine learning, digitalization, e-commerce, m-commerce, information systems, sustainable development, big data, IoT, and business analytics, aligning with the scope of this study.

With only fsQCA-related keywords, the initial result of the automated search was 1835 articles. Subsequently, by employing a search strategy defined with both fsQCA- and application-related keywords and applying the filtering criteria, we identified a total of 20 articles related to the scope of this review. This indicates that although fsQCA research has broadened vastly in various disciplines, it is still a new topic of technology-adapted decision-making applications. After excluding irrelevant studies based on the context, 14 articles were included in the final set.

### 3.3 Data extraction and data synthesis

In the data extraction, we primarily considered i) the focus of each paper using fsQCA, ii) the factors/variables examined, iii) the nature of the empirical data sample used, iv) other techniques used with fsQCA, and v) the key findings regarding the application context. In the data synthesis, we aimed to examine and summarize the insights from the selected articles to address the research questions defined in our study. Focusing on a thematic synthesis (Braun, 2006) using qualitative data, we performed a descriptive analysis to provide evidence from the related research in favor of the objectives and research questions defined in this review study.

# 4 Findings

## 4.1 An overview of the reviewed articles

The findings of the present review article are based on 14 articles. A summary of all reviewed articles in our study can be seen in Table 1, in which each row summarizes each study, its practical application (under categories: digital transformation, digital assistant, IoT, AI adoption, e-commerce, business analytics and information modeling, and machine learning), context (whether it is organization decision-making or consumer behavior study), methods (hybrid models are given with "+" ), underlying theory (i.e., guiding principles for research), and data sample (used in the empirical analysis).

**Table 1: An overview of reviewed articles**

| Study | Application | Context | Methods | Underlying theory | Data sample |
|---|---|---|---|---|---|
| Zhang et al. (2023) | Digital transformation | Organizational | fsQCA, PLS-SEM | TOE framework | Data from 236 construction enterprise managers |
| Fan et al. (2023) | Digital transformation | Organizational | NCL + fsQCA | TAM | Data from 80 respondents from petrochemical industry in China |
| Song et al. (2023) | Digital transformation | Organizational | fsQCA | TOE framework | Data from annual reports of 388 listed companies in China |
| Liu et al. (2023) | Digital transformation | Organizational | fsQCA | TOE framework | Data from multiple sources (e.g., Perinorm, Korean standards database, and Derwent database) |
| Sharma et al. (2022) | Digital assistant (Chatbot) | Consumer behavior | fsQCA, ANN, PLS-SEM | TAM | Survey data from a selected group of 345 millennials. |

| Study | Application | Context | Methods | Underlying theory | Data sample |
|---|---|---|---|---|---|
| Al-Emran et al. (2023) | Digital assistant (Chatbot) | Consumer behavior | fsQCA, PLS-SEM | TAM | Survey data from 447 respondents |
| Chen and Ye (2023) | IoT | Consumer behavior | fsQCA, PLS-SEM | TAM | Survey data focusing on the Chinese market |
| Chuah et al. (2021) | AI adoption (Service robots) | Consumer behavior | fsQCA | TAM | Survey data from 566 Taiwanese consumers |
| Bawack et al. (2021) | AI adoption (Voice shopping) | Consumer behavior | fsQCA, PLS-SEM | TAM | Survey data from 224 voice-shopping experienced citizens in US |
| Mustafa et al. (2022) | AI adoption (5G technology) | Consumer behavior | fsQCA, PLS-SEM | TAM | Survey data from 830 respondents in China |
| Hew et al. (2023) | E-commerce | Consumer behavior | fsQCA + ANN | TAM | Survey data from 1155 Malaysian mobile consumers |
| Hayajneh et al. (2022) | Business analytics | Organizational | fsQCA, PLS-SEM | ROT framework | Survey data from 450 respondents from large firms and SMEs in Saudi Arabia |
| Li et al. (2022) | Information modeling | Organizational | fsQCA, NCL | TAM | Survey data from 192 managers in SMEs |
| Costa-Climent et al. (2023) | Machine learning | Organizational | fsQCA | BMT | A data set from 122 European start-ups (Crunchbase, tweets) |

Table 1 shows that seven of the reviewed articles based on fsQCA are from an organizational context and seven from a consumer behavior context. The underlying theories of consumer behavior in technology adoption and organizational technology decision-making are often based on the technology acceptance model (TAM) and the technological-organizational-environmental framework (TOE). TAM focuses on understanding the factors influencing consumers' acceptance and adoption of new technologies (Chen and Ye, 2023). Besides, the TOE framework considers broader contextual factors influencing organizational technology adoption and implementation (Song et al., 2023). It considers not only technological factors but also organizational and environmental ones. However, two studies were based on different theoretical perspectives as mentioned in their studies; one was based on business model theory (BMT) (Costa-Climent et al., 2023), and the other was on resource orchestration theory (ROT) (Hayajneh et al., 2022). ROT examines how companies select, design, and configure resources and capacities to succeed in business (Hayajneh et al., 2022), whereas BMT focuses on how an organization develops and offers value to customers (Costa-Climent et al., 2023). The following subsections discuss more details of the empirical part and key findings of each study in consumer behavior and organizational contexts.

## 4.2 Consumer behavior towards technology adoption

Table 2 summarizes the factors considered in the empirical part and key results obtained using fsQCA (and other methods) in consumer behavior and technology adoption research. Note that all of these articles were based on the TAM theory.

**Table 2: Factors examined and key findings of fsQCA research in consumer behavior**

| Study | Tech solution | Factors considered | Key findings |
|---|---|---|---|
| Sharma et al. (2022) | AI-based Chatbot adoption for online purchasing | Human-likeness (perceived anthropomorphism, perceived social presence, perceived interactivity) and information quality | PLS-SEM, ANN→ Perceived interactivity has the strongest effect on the purchasing intentions.<br>fsQCA→ Perceived interactivity, perceived anthropomorphism, perceived social presence are core conditions for influencing purchasing intentions. |
| Al-Emran et al. (2023) | AI-based Chatbot adoption for knowledge sharing | Performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, habit | PLS-SEM→Social influence, facilitating conditions, and hedonic motivation have no impact on the chatbot use.<br>fsQCA→All factors might have an impact. |
| Chen and Ye (2023) | Smart clothing adoption | Perceived usefulness (PU), perceived ease of use (PEOU), attitudes (ATTs), functionality (FUN), expressiveness (EXP), aesthetics (AES) | PLS-SEM→ All FUN, EXP, AES influence PEOU, EXP does not significantly affect PU, PU and PEOU positively affect ATTs, and PU and ATTs positively influence purchase intentions.<br>fsQCA→ The combination of FUN, AES, PU, and ATTs could be the best option to achieve a high level of smart clothing purchase intentions. |
| Chuah et al. (2021) | Service robot adoption | Human-likeness (anthropomorphism, perceived intelligence), technology-likeness (performance | None of these factors were found to be either necessary or sufficient in achieving high-level of behavioral intention. Instead, four causal combinations serve as sufficient to boost consumers' intention to use service robots. |

| Study | Tech solution | Factors considered | Key findings |
|---|---|---|---|
| | | expectancy, hedonic motivation, privacy risks), personalities (extraversion, openness) | |
| Bawack et al. (2021) | Voice shopping adoption | Personality traits (extroversion, agreeableness, conscientiousness, emotional instability, intellect), privacy concerns, trust smart speaker manufacturer, prior experience with smart speakers | PLS-SEM→ Trust and privacy concerns as mediators between personality traits and voice shoppers' perceptions of customer experience. fsQCA→ key combinations of these factors that lead to high customer experience performance. |
| Hew et al. (2023) | Mobile-commerce applications | Barriers (image, risk, tradition, usage, value), resistant behavior (rejection, oppositions, postponement) | All resistant barriers matter but are not equally important in causing resistant behavior. Image, usage, value, and risk barriers were found to be core conditions, but tradition barrier was a peripheral condition. |
| Mustafa et al. (2022) | 5G technology adoption | Intrinsic factors, psychological factors, social factors, economic factors, health consciousness, behavioral intention | PLS-SEM→Economic factors are not statistically significant to 5G technology adoption. fsQCA→Economic factors are vital for 5G technology adoption. Also, six configurations to achieve high 5G adoption were identified. |

Conversational commerce is becoming increasingly popular as a powerful communication method to improve online purchasing (Sharma et al., 2022). According to Tables 1 and 2, Sharma et al. (2022) assessed the effects of digital assistant (e.g., AI-based chatbot) attributes on purchasing intentions using a combined approach of fsQCA, artificial neural networks (ANN), and partial least squares-structural equation modeling (PLS-SEM). Among the factors investigated, the result with fsQCA demonstrated that perceived interactivity, perceived anthropomorphism, and social presence are the core conditions for influencing the purchasing intentions of millennials. Al-Emran et al. (2024) also used a combined approach using fsQCA and PLS-SEM to examine factors influencing chatbots for knowledge sharing in education. The empirical analysis evaluated the positive effects of the factors considered. fsQCA showed that all factors might impact chatbot use, while PLS-SEM identified social influence, facilitating conditions, and hedonic as having no impact on chatbot adoption.

A recent study by Chen & Ye (2023) used both fsQCA and PLS-SEM to explore key factors influencing consumers' intentions in purchasing smart clothing. The factors, PU, PEOU, ATTs, and three external factors, FUN, EXP, and AES, were considered effects for consumers' purchasing behavior of smart clothing. The empirical study, using the fsQCA approach, examined six different configurations of those factors. The fsQCA results revealed that combining FUN, AES, PU, and ATTs could be the most suitable option for achieving high smart clothing purchase intentions. Moreover, Chuah et al. (2021) studied how factors such as human-likeness, technology-based, and consumer personalities interact as causal configurations to influence the intention to use robotic services.

The fsQCA results showed that individual factors alone are not enough for high intention levels, but four combinations were identified as sufficient to improve consumers' intention to use service robots. Bawack et al. (2021) examined how personality traits, privacy concerns, trust, and prior experiences affect customer experience performance in voice shopping. They used both PLS-SEM and fsQCA methods to explore how the combinations of these factors could contribute to high customer experience performance. PLS-SEM results depicted privacy concerns and trust as mediators between personality traits and customer experience perceptions. fsQCA results identified key combinations of these factors leading to high customer experience performance.

Furthermore, a recent attempt by Hew et al. (2023) used a hybrid approach based on fsQCA and ANN to examine three different forms of resistance behavior considering five different barriers exhibited by mobile consumers towards using mobile-commerce applications. The results showed that all active innovation resistance barriers are relevant but not equally significant in triggering resistance behaviors. Mustafa et al. (2022) investigated various factors influencing consumers' decision-making in 5G technology adoption using a fsQCA-based approach. This study examined direct and indirect influences from intrinsic factors (perceived performance, perceived functional value, perceived value), psychological factors (satisfaction, habit, hedonic motivation, curiosity), social factors (social influence, environmental knowledge, and environmental awareness), economic factors (cost value, facilitating conditions), health consciousness, and behavioral intention to 5G adoption. The findings with PLS-SEM indicated that economic factors are not significant in 5G technology adoption, contrasting with fsQCA, which identified that economic factors are vital and suggested six key combinations of those factors to achieve high 5G technology adoption. These studies are great examples of fsQCA as a suitable approach for examining complex and nonlinear relationships among variables/factors in consumer behavior and technology adoption research.

### 4.3 Organizational technology decision-making

Table 3 summarizes fsQCA-based research studies in organizational technology decision-making, focusing on the application context, the factors considered in the empirical part, and key results. Note that studies by Zhang et al. (2023), Song et al. (2023), and Liu et al. (2023) were originated from the TOE framework, while those by Fan et al. (2023) and Li et al. (2022) from TAM. The studies of Hayajneh et al. (2022) and Costa-Climent et al. (2023) aligned with ROT and BMT frameworks, respectively. In addition, some studies, such as Li et al. (2022), Hayajneh et al. (2022), and Costa-Climent et al. (2023), focused on the individual firm level, while the rest focused on the organizational level.

**Table 3: Factors examined and key findings of fsQCA research in organizational context**

| Study | Application context | Factors considered | Key findings |
|---|---|---|---|
| Zhang et al. (2023) | Digital transformation in construction industry | Use of digital technology, digital employees, relative advantage, competitive pressure, partner pressure, policy support, digital cost, organizational readiness, digital transformation strategy, top management support | PLS-SEM→Seven factors that significantly affect on digital transformation.<br>fsQCA→Three configuration paths that can achieve high-level digital transformation.<br>Both→Top management support and policy support are key factors in the dual effect. |
| Fan et al. (2023) | Digital transformation in manufacturing | Digital transformation of product, organizational, service, process, and model | A combination of three driving paths was recognized to achieve high sustainable innovation capability and four conditional configurations were found to lead to non-high sustainable innovation capability. |
| Song et al. (2023) | Digital innovation in enterprises | R&D investment, high-level talents, organizational size, top management team | Three and two types of configurations from organizational, and environmental conditions are |

| Study | Application context | Factors considered | Key findings |
|---|---|---|---|
| | | heterogeneity, industrial development speed, regional digitalization level | found to drive high digital innovation intention and performance, respectively. |
| Li et al. (2022) | BIM adoption in architecture, engineering, and construction industry | Perceived business value of BIM, perceived benefits, perceived costs, perceived risks, perceived resource availability | NCA→high perceived resource availability and high-performance expectancy (PE) are necessary conditions for high BIM adoption intention.<br>fsQCA→high PE is the single core condition for high AI. Also three configurations of managers' psychological factors were identified as influencial. |
| Hayajneh et al. (2022) | Use of business analytics (BA) | Business analytics capability, $\pi$-shaped skills | fsQCA→ BA and $\pi$-shaped skills are sufficient but not necessary for high innovative performance.<br>PLS-SEM→ BA and $\pi$-shaped skills are relevant antecedents for innovative performance but their combination did not hold. |
| Costa-Climent et al. (2023) | Use of machine learning technology | Total funding, novelty, utility, performance, efficiency | Start-ups focusing on both efficiency and novelty in their ML technology are more likely to create and appropriate value. |
| Liu et al. (2023) | Technology standard competitiveness (TSC) in the AI industry | Technological innovation ability, academic research intensity, government responsiveness, organizational participation, international competitive pressure, market size | Four configurations that lead to high-TSC. Among them, high academic research intensity and high market size are the key factors. |

Digitalization drives substantial industry changes and is recognized globally as crucial for traditional competitiveness (Zhang et al., 2023). Accordingly, extensive research already exists on the impact mechanism of digital transformation across diverse fields. As Tables 1 and 2 display, using a hybrid model that combines fsQCA and PLS-SEM, Zhang et al. (2023) studied TOE factors affecting digital transformation in construction enterprises from a dual-effect perspective. The fsQCA result revealed three configuration paths leading to high-level digital transformation activity, while both methods suggested that top management and policy support are the key factors from a dual perspective.

Fan et al. (2023) also analyzed the different types of digital transformation in improving sustainable innovation ability in manufacturing firms by using a mixture model of NCL (also referred to as necessary condition analysis) and fsQCA methods. This analysis with fsQCA + NCL highlighted that integrating three types of digital transformation can effectively boost sustainable innovation in manufacturing firms: pure product-focused, model + organizational, and comprehensive digital transformation paths. Son et al. (2023) investigated the influence of six factors from the TOE framework on enterprise digital innovation using the fsQCA approach. The results with fsQCA identified different configuration paths based on technology-organization-environment types, which drive high digital innovation intentions and performance. Moreover, Li et al. (2022) examined how managers' psychological factors influence their decisions regarding adopting building information modeling (BIM) from their perspectives. By using survey data from 192 managers in SMEs, the fsQCA analysis identified high-performance expectancy (PE) as the primary condition for high BIM adoption intention (BIM-AI), while NCL indicated that both high perceived resource availability and PE are necessary conditions for high BIM-AI. Additionally, three configurations of managers' psychological factors, reflecting their decision preferences: loss aversion, benefit preference, and risk avoidance, were revealed by fsQCA analysis.

Several authors have applied fsQCA approaches to assess the impact of data analytics and ML on firms' innovative and improved performance.

Using fsQCA and PLS-SEM methods, Hayajneh et al. (2022) examined how business analytics and $\pi$-shaped skills impact a firm's innovative performance while exploring the moderating influence (in terms of big data and analytics) of $\pi$-shaped[1] skills. The results from fsQCA indicated that though business analytics and $\pi$-shaped capabilities contribute to high innovative performance, they are not necessary conditions. With a focus on how start-ups apply ML technology for success, Costa-Climent et al. (2023) utilized a fsQCA-based model to examine how a firm's business model design interacts with different factors to illustrate value creation and appropriation using ML. The empirical analysis offered a holistic view from multiple theoretical perspectives on how start-ups can strategically leverage ML technologies

[1] $\pi$-shaped skills represent agility and adaptability, enabling value creation and a competitive edge (Hayajneh et al., 2022).

for value creation and capture. Additionally, one of the key findings was that start-ups equipped with both funding and a high degree of novelty in their ML technology are better positioned to create value than start-ups with only one type of these factors. Lastly, Liu et al. (2023) applied the fsQCA approach to study the complex factors influencing technology standard competitiveness (TSC) within the AI industry and to identify multiple equivalent paths that jointly support TSC. The findings revealed no necessary conditions, but four different configuration paths sufficiently led to achieving high TSC. Among them, high academic research intensity and high market size were core factors yielding national high TSC.

## 4.4 Other methods used with fsQCA

Looking at Table 1, we can observe that a few other methods, such as ANN, NCL, and PLS-SEM, have also been employed with fsQCA to enrich their empirical analysis and findings. Among them, fsQCA with PLS-SEM has been frequently combined, indicating the importance of integrating PLS-SEM with fsQCA in analyzing complex cases. Let us present some implications given by each study regarding the value added by fsQCA when used with the PLS-SEM method.

PLS-SEM is a well-known statistical approach that can model relationships from the independent variables to the desired outcome and identify key influential variables (Sharma et al., 2022). The PLS-SEM approach is considered symmetric (Al-Emran et al., 2023; Hew et al., 2023), indicating the ability to reveal linear relationships. As Chen and Ye (2023) stated, symmetric methods can analyze individual and net effects of the variables on the dependent variable but not non-linear relationships. Given this, Mustafa et al. (2022) and Sharma et al. (2022) showed the necessity of using a second stage of analysis when PLS-SEM is applied because PLS-SEM analysis may examine only linear relationships within the given research design and may not sufficiently predict outcomes of a complex decision-making process. They performed fsQCA-based second-stage analysis to mitigate the issues of PLS-SEM and achieve improved performance by analyzing non-linear relationships. This is because the fsQCA approach is considered an asymmetric approach (Al-Emran et al., 2023; Hew et al., 2023; Chen and Ye, 2023), allowing for identifying complex configurations of factors leading to specific outcomes. Similarly, Al-Emran et al., 2023 used fsQCA as the second stage method and demonstrated the value of the use of asymmetric analysis (fsQCA) and the danger of based only on symmetrical analysis (PLS-SEM). Bawack et al. (2021) highlighted that fsQCA can identify unique and new insights considering complex situations by addressing the issue of the overly simplistic nature of hypotheses tested using traditional methods. Therefore, they have also employed fsQCA to explore crucial relationships between consumers' perceptions of voice shopping adoption, which cannot be identified using the PLS-SEM approach. Chen and Yu (2023) has applied both PLS-SEM (to investigate individual effects of each antecedent) and fsQCA (to examine the effect of causal configurations) to deliver more accurate insights in the analysis of complex factors considering consumers' purchasing intentions.

### 4.5 Novel insights and unique properties offered by fsQCA

Applying fsQCA in various studies has provided novel insights into complex causal relationships that traditional regression-based methods may fail to reveal. For example, in Hayajneh et al. (2022), while PLS-SEM did not support the theory of interaction between business analytics capabilities and $\pi$-skills, fsQCA revealed that combining them is crucial for innovation. The incorporation of complexity theory and configuration analysis, as illustrated by Li et al. (2022), further demonstrated the efficacy of fsQCA in uncovering complex patterns of causal interrelationships between managers' psychological factors and decision-making. The ability of fsQCA to identify effects caused by unobserved heterogeneity, as highlighted by Hayajneh et al. (2022), makes it more valuable than traditional methods, especially in handling continuous data types and interval scale variables, as noted by Song et al. (2023), Chuah et al. (2021), and Bawack et al. (2021). Liu et al., 2023 stated that fsQCA is not affected by variable deviations or outliers because it does not rely on underlying hypotheses, specific explanatory variables, or correlation analyses. Moreover, unlike symmetric methods, Zhang et al. (2023), Liu et al. (2023), and Sharma et al. (2022) emphasized the efficacy of fsQCA in revealing multiple conditions/paths instead of relying on a single factor/relation. Mustafa et al. (2021) argued that while traditional variance-based methods capture major effects, fsQCA drives deeper into complex, asymmetric relations, revealing influential combinations of pychological, social, economic, and health consciousness factors on 5G technology adoption. Particularly in consumer research, where asymmetric relationships and non-linearities are prevalent, Hew et al. (2023), Al-Emran et al. (2023), and Chen and Yu (2023) further demonstrated the practical use of fsQCA. Overall, the fsQCA could be a valuable tool for researchers seeking to explore complex causal mechanisms and uncover valuable insights that traditional methods may overlook.

## 5 Discussion and future implications

This review study covered two specific application areas of fsQCA: consumer behavior and technology adoption, as well as organizational technology decision-making from a technological perspective. It is worth noting that the most common underlying theory for each study was either the TAM or the TOE framework, indicating their widespread use in the field. It was evident that, by employing fsQCA, researchers can analyze various factors influencing adoption decisions, such as perceived usefulness, perceived ease of use, attitudes, social influence, and economic considerations, particularly in consumer behavior research. More importantly, fsQCA has allowed for the identification of multiple causal configurations that lead to achieving high performance of desired outcomes. It has especially identified different configurations of TOE factors in organizational decision-making studies, which lead to high or low levels of adoption intentions and reveal valuable insights. This reflects the efficacy of the fsQCA method in capturing the complexity inherent in the context studied and supports identifying the nonlinear relationships and interactions among these factors, providing a more holistic understanding of consumer behavior and organization technology decision-making processes.

Furthermore, a combination of fsQCA with PLS-SEM has been frequently applied, highlighting the importance of integrating PLS-SEM with fsQCA in analyzing complex cases. It is also worth mentioning that the empirical analysis of most studies was based on survey data. This is because the survey data allows for direct insights from stakeholders, such as consumers and industry professionals, providing the relevance and applicability of research findings in real-world contexts directly. Another interesting finding was that the publication year of most related studies was 2022 or 2023, indicating that this field of research using fsQCA is still a relatively new topic of interest but will likely continue to be researched in the upcoming years.

Future research could explore novel applications of fsQCA in emerging fields, such as AI ethics, cybersecurity, and digital governance, as well as generative AI and e-business platforms, to address complex challenges and inform evidence-based policymaking and organizational strategies. Additionally, methodological advances and hybrid models can further enhance the application of fsQCA as a robust analytical tool for identifying the complexities of digitalization and facilitating sustainable development.

## 6 Conclusions and limitations

In this study, we investigated the applications of fsQCA in previous studies that focused on examining performance and human behavior regarding technology adoption, and organizational technology decision-making contexts. Based on the review results of the 14 selected articles, it is evident that empirical studies utilizing fsQCA have successfully provided significant insights into each practical application. Additionally, the fsQCA has demonstrated its capability to identify necessary and sufficient conditions for each case evaluated. One limitation of this study was the dependence on a single database (WoS) for article search, which might have left some related studies out. Also, relevant research might have been missed due to the need for specific keywords fitting the article's focus. However, given the scope of this study, we believe that we have compiled a reasonably comprehensive set of articles for this review. Nevertheless, this review paper illustrates how fsQCA has been a valuable tool, particularly in technology transition and decision analytics studies. Hopefully, this paper could inspire further research into investigating the factors influencing various types of technology adoption and decision-making processes using fsQCA approaches.

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