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The configurational effects of task-technology fit, technology-induced engagement and motivation on learning performance during Covid-19 pandemic: An fsQCA approach

Alev Elçi[1] · A. Mohammed Abubakar[2]

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Abstract

At the onset of 2020, Covid-19 pandemic began and disrupted teaching and learning activities with substantial implications for resources and operations. Against this backdrop, the configural causal effects of task-technology fit, technology-induced engagement and motivation, gender, and residential location on learning performance are examined. The proposed association was tested with a dyad sample of faculty members and students (n = 16) using fuzzy sets (fsQCA) analysis. Results show that (i) task-technology fit, and technology-induced motivation emerge as necessary conditions for high learning performance; (ii) task-technology fit, technology-induced engagement and motivation are sufficient conditions for high learning performance among female students, (iii) task-technology fit, technology-induced engagement and motivation are sufficient conditions for high learning performance among students living in urban areas and (iv) task-technology fit is a sufficient condition for high learning performance among female students living in rural areas irrespective of technology-induced engagement and motivation. Implications for theory and policy prescriptions are offered for practitioners.

Keywords Coronavirus pandemic · Digital-mediated learning · Faculty development · Technology · Learning performance · Motivation · Technological tasks · Formative effects

✉ A. Mohammed Abubakar
Mohammed.abubakar@antalya.edu.tr

Alev Elçi
dr.alevelci@gmail.com

1 Aksaray University, Aksaray, Turkey

2 Antalya Bilim University, Antalya, Turkey

1 Introduction

At the start of 2020, governments and civil society around the world were discussing issues and challenges pertaining to higher education. Some of which are to provide access and educate students from low income and disadvantaged minorities, develop a more stalwart and sagacious commitment towards sustainable development goals for the betterment of faculty members and students welfare (including physical, social and mental health as well as nutrition). However, Covid-19 pandemic altered these plans, and other pressing issues were prioritized. From the perspective of higher education Covid-19 is a dizzying historical event that altered teaching, learning, research, and work sociology as activities had to be conducted online. These changes did not only disrupt the conventional teaching and learning activities, but also reveal the inequalities between individuals with digital infrastructure and resources and those without access.

There are various factors that have a significant impact on students' learning performance. Task-technology fit (TTF) has been illustrated as the extent to which a technology does or could meet task needs (Goodhue & Thompson, 1995). The use of technology in learning is mostly viewed as resource-integration or new procedure to facilitate learning activities and outcomes (Rai & Selnes, 2019). In this paper, the scope of TTF is grounded on the extent to which technology facilitated students learning activities during the pandemic. In other words, TTF reflects how technology usage of software and application programs such as Learning Management Systems, Adobe Connect, MS Teams, Zoom and Loom during the pandemic assist students to attain learning performance. Student learning achievements and performance have been linked with the level of motivation and engagement in recent studies (Domen et al., 2020; Lin et al., 2018). Studies claimed that learning motivation can be increased with the help of technology products or media (Haste & Hogan, 2012). Consequently, the technology-induced engagement (TIE) and technology-induced motivation (TIM) serve as facilitators for learning outcome and performance (Garcia-Cabot et al., 2020; Heflin et al., 2017).

Research findings posited that *socio-economic* variables are key indicators for educational opportunities and inequality in Turkey (Gezer & İlhan, 2018). Besides the other variables determined in order of importance are *residence*: rural (i.e., villages, towns, and small settlements) or urban (i.e., metropolis), *parental characteristics*, *disability*, *geographical region*, *mother tongue*, *gender*, *number of children* in a household, *technological facilities*, *religion and beliefs*, and lastly *ethnic origin*. The Turkish Statistical Institute published *Household Information Technology Usage Survey*; reported an Internet usage of 79.0% for people between 16 and 74 ages, and the rate was 84.7% for men higher than that of women 73.3% (TurkStat—TÜİK, 2020). Caner et al. (2015) also claims that conservative perceptions on gender roles are usually reflected in public speeches. Yükseltürk and Bulut's (2009) study which was focused on gender differences in self-regulated online learning environments found that there was no statistically significant difference among self-regulated learning components, motivational beliefs, and learning achievements with respect to gender. Besides "self-efficacy for learning and performance, and task value demonstrated a significant amount of variance in male students' achievement" (Yükseltürk & Bulut, 2009).

This paper contributes to existing literature in four distinct ways. *First*, it provides empirical evidence on the importance of task-technology fit (TTF) when the world unexpectedly migrated to online teaching platforms. *Second*, since expert opinions assert the presence of gender and settlement induced digital divide during Covid-19 pandemic (Mlambo-Ngcuka & Albrectsen, 2020), this paper strives to confirm this theory empirically. *Third*, the paper also examines the combined influence of task-technology fit (TTF), technology-induced engagement (TIE), technology-induced motivation (TIM), gender, and residential location on student learning performance during Covid-19 pandemic. *Fourth*, this paper identifies potential ways and remedies for faculty development in relations to technology usage during and in the post pandemic era.

Fifth and last, this paper opts for fuzzy sets Qualitative Comparative Analyses (fsQCA) because conventional methods such as regression, linear models and variants thereof (e.g., structural equation modeling) routinely fail to address theory testing adequately (Woodside, 2013) due to their strict net effects assumptions. fsQCA overcomes the net effect weakness and allows for multiple variables (causal configurations) which ensure a more plausible explanation. More subtly, fsQCA allows a rather direct and more "managerial" interpretation of outcomes, as an example a student may have high performance or not, without statistical confusion based on probability (Ragin, 2009; Woodside, 2013).

The rest of the study is organized as follows. In Sect. 2, literature review and propositions are presented, alongside the conceptual model and research question. Section 3 illustrates the research methods, materials, and procedures, while Sect. 4 presents fsQCA analytical implementations and results. Finally, Sect. 5 discusses the findings highlighting administrative and theoretical practical implications and concludes with limitations and avenues for future research.

2 Literature review and propositions

2.1 Task-technology fit and learning performance

Task-technology fit (TTF) "is the degree to which a technology assists an individual in performing his or her portfolio of tasks" (Goodhue & Thompson, 1995, p. 216). It designates the interdependence among task, technology, and individuals (Yüce et al., 2019). Simply, it is the correspondence between task requirements, individual abilities, and the functionality of the technology. In this study, TTF is all about the extent to which the use of a technology supports users in performing their coursework during Covid-19 pandemic. Since its inception, several researchers have applied the TTF model in predicting and explaining user behavior, net advantages, job-related duties, and school coursework performance. Scholars found that TTF exerts significant influences on learning performance (Lee & Lehto, 2013; Yüce et al., 2019). These outcomes have received empirical support and validation from prior work and meta-analysis that discovered a positive association among TTF and personal performances (Cane & McCarthy, 2009; Isaac et al., 2019; Lin, 2012). Digitalized platforms should not be ideated as a mere utility, but as a medium for learning amid Covid-19 pandemic. This paper posits that TTF amid Covid-19 pandemic is likely to be a causal condition for learning performance.

2.2 Technology-induced engagement and learning performance

According to Cole and Chan (1994), student engagement is "the extent of student involvement and active participation in learning activities" (p. 259). The amount of physical and psychological energy that a student devotes to academic and/or learning activities in the university can also be conceptualized as student engagement (Osatuyi & Passerini, 2016). As a result of Covid-19 pandemic, teaching and learning activities are now carried out in digital spaces. It has become critical to understand the association between TIE and learning performance. Several studies conducted prior to Covid-19, found that students' engagement creates a more supportive learning culture using technology (Heflin et al., 2017). In that, social gamification appears to stimulate student engagement and motivation which in turn electrifies learning achievements (Garcia-Cabot et al., 2020). Consequently, Sun (2014) showed that the use of clickers also could help to increase learners' engagement and attention, and student's engagement happens to be a determinant for learning performance (Chen, 2017). Building on this line of arguments, this paper posits that TIE amid Covid-19 pandemic is likely to be a causal condition for learning performance.

2.3 Technology-induced motivation and learning performance

Motivation is a multifaceted concept, with interest, autonomy and competence. *Interest* is governed by basic human needs such as *competence* and *autonomy*. *Autonomy* refers to "regulating one's own behavior and experience and governing the initiation and direction of action" (Ryan & Powelson, 1991, p. 52). *Competence* is "a need for challenge and feelings of effectance" (Ryan et al., 2006, p.349). While using varieties of technologies for learning amid Covid-19, students should have a sense of autonomy (e.g., to access, read, collaborate) with peers online. Besides autonomy, students should also feel a sense of competence. That is, having the perception and ability to accomplish their school related tasks. Indeed, the satisfaction of those needs' fosters *interest*, which leads to better outcomes (Chen & Law, 2016). Past empirical work shows that the three basic human needs as facets of motivation (i.e., autonomy, competence, and interests) are strong antecedents for positive learning outcomes (Vansteenkiste et al., 2004).

Motivation is a concept that electrifies, stimulates, directs, and sustains behavior allowing students to engage in discovery behavior or learning. According to Yüce et al. (2019), motivation is a critical element for learning that impacts the outcome of educational technology. Motivation is a determinant for students' achievement and performance (Law et al., 2019). Digital technology motivation associated with digital technology and innovation were shown to influence academic achievements

(Rashid & Asghar, 2016). Digital-mediated learning environments that motivate the students are more likely to create pathways for higher academic performance (Kangas et al., 2017). Since motivation is a vital factor in students' learning performance, this paper posits that TIM amid Covid-19 pandemic is likely to be a causal condition for learning performance.

2.4 Gender and learning performance

The association between gender and learning performance is inconclusive. A body of research has documented that males are more likely to excel compared to females, especially achieve higher mathematics and science test scores on assessment of college, university, and graduate program admission (Halpern et al., 2007). While others documented that females are more likely to excel compared to males (Volchok, 2018). Zengin-Arslan (2002, p. 400) emphasizes "This gendered segregation in technical professions points to the fact that the dominant discourse in technology is masculine." But Smith and Dengiz's (2009) study showed that the Turkish women in engineering claimed to choose their profession since they enjoy the mathematics and science foundation. However, in their review paper concerning gender differences in educational performance in developed and developing nations, Ullah and Ullah (2019) asserts that "the discourse of boys' outperformance in education that once existed has now been shifted to girls' outperformance" (p. 163).

According to Halpern et al. (2007) "there are no single or simple answers to the complex questions about sex differences in science and mathematics". Similarly, Martí-Ballester (2019) discovered that most of the observable factors influencing students' academic performance is gender invariable. Contrariwise, other scholars argued that the gap between women and men using the Internet and mobile phones is significant (Bimber, 2000). A recent OECD report noted that affordability, lack of awareness, education and technological literacy entwined with structural biases and socio-cultural norms are the root causes of gender-based digital exclusion (OECD, 2018). Covid-19 pandemic forced countries to rely on digital services to reduce the spread, based on this scenario men are more likely to benefit disproportionately due to greater access to valuable information. While, lack of access to digital tools and services by young girls and women will make them fall behind, which subsequently widen the existing gender inequalities. Building on this line of arguments, this paper posits that gender amid Covid-19 pandemic is likely to be a causal condition for learning performance.

2.5 Residential location and learning performance

COVID-19 new normalcy has echoed and showed the big picture of digital divides. Iivari et al. (2020) argued that students are not equal in terms of digitized education engagement, due to technology access and use, and polarizations of digital skills development. Research found that rural areas and less prosperous regions in most countries have poor digital technologies infrastructures, and that their income affects their ability to purchase ICT services (Song et al., 2020). The World Bank (2020) report also shows that rural and less affluent regions are subject to digital divide due to lack of ICT infrastructure and slow Internet connections. This reduces ICT investments and further widens the digital divides. Using publicly Internet search data in the US, Bacher-Hicks et al. (2020) found that schools in urban areas with high income and better Internet connection had an increase in search intensity to sought out online learning resources. The same cannot be said for rural areas. Building on this line of arguments, this paper posits that settlement or residential location amid Covid-19 pandemic is likely to be a causal condition for learning performance. Based on the extant theoretical and empirical abstractions, the following research question is proposed:

Research question What conditions of task-technology fit (TTF), technology-induced engagement (TIE), technology-induced motivation (TIM), gender and residential location (rural versus urban) are sufficient or necessary to create causal combinations that explain high students learning performance. See Fig. 1.

3 Methodology

3.1 Sampling and procedures

The present study employed a convenience and snowball sampling technique by recruiting faculty members (instructors/lecturers) who participated in a faculty development workshop in 2016. The workshop consisted of sessions where participants were introduced and taught how to use technology-enhanced learning

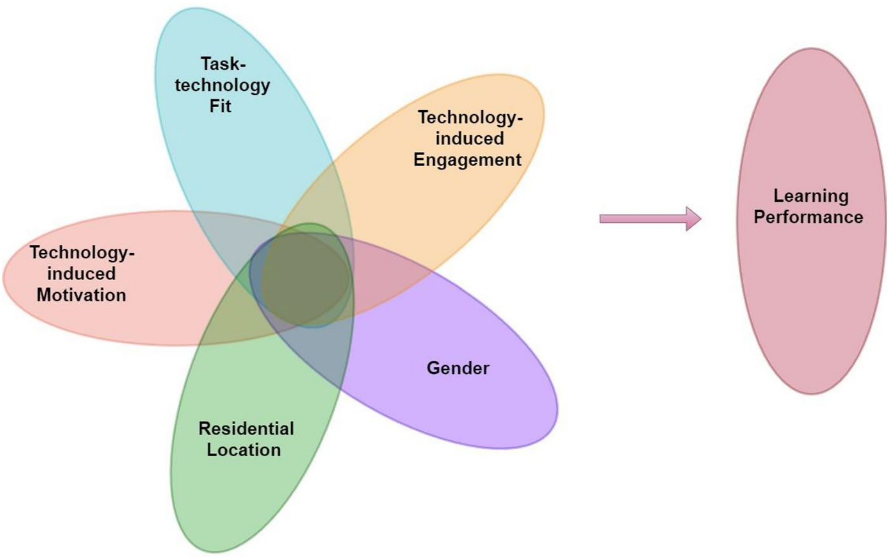

Fig. 1 Configural model

platforms such as Kahoot, Adobe Connect, Weebly, PowToon and others in teaching and learning activities (Elçi et al., 2016). Over four years have passed since the workshop, Covid-19 pandemic shut down the higher educational sector overnight. The pandemic has confronted the sector with unprecedented challenges. Strategies to flatten and soften these adverse effects include online and distance learning, in lieu of these developments. The workshop participants and their students were surveyed, who have embraced the above said tools during the pandemic.

Dyadic surveys are utilized for extensive analysis of intra- and inter-personal mechanisms of social actors such as husband-wife, doctor-patient, and parent–child (Eisikovits & Koren, 2010). Dyadic surveys are useful for disconfirming evidence in data and abates the risk of an incomplete understanding of a context (Abubakar et al., 2019; Schrodt, 2015). Since it is not very often used in teacher-student relationships, this sampling may be considered as a pioneer. Additionally, dyadic data measurements "reflect not only the characteristics of the person providing the data, but also those of the partner and causation that occurs as a result of mutual interaction" (Abubakar et al., 2019, p. 17). Multi-sourced data are known to be robust towards common method bias (MacKenzie & Podsakoff, 2012). Participating faculty members were asked to recommend a student to complete the survey section pertaining to TTF, TIE and TIM. Afterwards, the faculty members were asked to rate the students' learning performance. Participation was completely voluntary, both students and faculty members were asked to confirm their consent and were told that they can discontinue at any point.

Responses were anonymous to minimize social desirability bias of the participants (MacKenzie & Podsakoff, 2012). Twenty-five (25) workshop participants were asked to take part, some declined due to time and family constraints, others either didn't teach during the pandemic or had left the university and were unreachable. A total of 16 dyadic data was obtained from students and faculty (one-to-one) at the end of 2019–2020 spring semester. In their influential work, Greckhamer et al., (2013) emphasized that fsQCA was designed for small samples as well as large sample settings. For small sample settings, 12 to 50 cases (sample size) are adequate and a minimum of 4 and maximum of 8 causal conditions can be modelled using 1 or 2 frequency thresholds. Therefore, 16 dyadic cases (sample) seem to be appropriate and sufficient for fsQCA analysis (Marx, 2010).

4 Research instruments

There are four instruments used in this research study: TTF, TIE, TIM and students' learning performance. TTF *(reported by students)*—was measured using a six-item scale developed by McGill and Klobas (2009) and adopted by Yüce et al. (2019). TIE *(reported by students)*—was measured using a three-item scale (Mejia, 2020). TIM *(reported by students)*—was measured using a five-item scale that captures both intrinsic and extrinsic learning motivations (Hsia et al., 2016). *Learning performance (reported by faculty members)*—was measured using a four-item scale developed by Van Raaij and Schepers (2008) and adopted by Yüce et al. (2019). The items were customized to meet the aim of this study and anchored on a 1 to 5-point Likert scale. The collected data was analyzed using fsQCA Software version 3.0.

4.1 Demographic properties

The demographic data from students include age, gender, program, study major, and residential location/area (rural vs. urban) during Covid-19 pandemic. Gender, age, and years of service are the captured demographic data of the participating faculty members. See Table 1.

5 Analytical approach and results

5.1 Fuzzy sets approach

FsQCA is a set theoretical analytical technique designated for case-oriented exploration and complex causational models characterized as having asymmetric and configurational equifinality properties (Fiss, 2011; Mikalef & Krogstie, 2020). Classical methods such as correlation and regression analyses are based on "ceteris paribus assumption", that only considers the contribution of a predictor

Table 1 Demographic breakdown

Students	#	%	Faculty Members	#	%
Gender			Gender		
Female	9	56.3	Female	12	75.0
Male	7	43.8	Male	4	25.0
Age			Age		
18–22	11	68.8	25–36	5	31.3
23–27	3	18.8	37–46	7	43.8
33 and above	2	12.5	47–56	3	18.8
			57 and above	1	6.3
Enrolled degree program			Academic Service Years		
Associate Degree	2	12.5	6–10	4	25.0
Bachelor's Degree	11	68.8	11–15	4	25.0
Graduate Degree	3	18.8	16 and above	8	50.0
Major					
Social Sciences	10	62.5			
Engineering & Technology	4	25.0			
Medical & Health Sciences	1	6.3			
Others	1	6.3			
Residential Location amid Covid-19					
Rural Area (districts, villages)	7	43.8			
Urban Area (city, metropolitan area)	9	56.3			

variable on the outcome variable and every other thing remains constant. These assumptions can be misleading and may result in equivocal research outcomes. Correlation and regression-based analysis cannot identify in which situations a variable has more (or less) influence on the outcome, because of its emphasis on the net effect of a variable without accounting for the relevance of other variables. In other words, classical methods cannot both detect complementarity and equifinality (Kaya et al., 2020; Woodside, 2014).

FsQCA is designed to support causal asymmetry, synergistic effects and equifinality assumptions. Complementarity occurs when causal conditions are organized (e.g., present or absent conditions) and/or interact to predict a higher level of an outcome as opposed to the net effect of all attributes (as isolated items), that determines the outcome. Consequently, equifinality occurs in situations where two or more paths (a combination of causal factors) exist to predict the same level of an outcome (Fiss, 2011). These paths (or configurations) in fsQCA may include both necessary and sufficient conditions, which may appear as present or negated (i.e., not present/absent) on a solution. Both necessary and sufficient conditions may be present (or absent) as core conditions, indicating a strong causal relationship with the outcome, or as peripheral conditions, indicating a weaker relationship with the outcome (Fiss, 2011; Ragin, 2009). The first step in fsQCA analysis is calibration, followed by necessity and sufficiency analyses.

5.2 Calibration

In the calibration stage, the research variables are converted into fuzzy sets as evident in Table 2. Calibration is the degree to which cases belong to a membership e.g., 'full membership = 1', 'cross-over point = 0.5' and 'full non-membership = 0'. Since our study uses a 5-point Likert scale, the study variables were rescaled following prior empirical research (Fiss, 2011; Mikalef et al., 2019) guidelines where 4 = full membership; cross-over point = 3; and 2 = full non-membership. fsQCA can be applied to crisp (i.e., binary) sets, fuzzy sets, and to mixtures of fuzzy and crisp sets (Ragin, 2009). Thus, in this study gender and residential location were treated as crisp sets (See Table 2).

Table 2 Calibration and measures reliability

	F-in	CO	F-out	Mean	SD	α
Task-technology fit	4.00	3.00	2.00	4.30	0.51	0.75
Technology-induced engagement	4.00	3.00	2.00	3.50	0.98	0.80
Technology-induced motivation	4.00	3.00	2.00	4.11	0.63	0.57
Students learning performance	4.00	3.00	2.00	3.28	0.77	0.72
Gender	1.00	N/A	0.00	0.56	0.51	N/A
Residential location	1.00	N/A	0.00	0.44	0.51	N/A

F-in Full membership; *CO* Cross-over; *F-out* Full non-membership; *SD* Standard deviation; *α* Cronbach's alpha

Table 3 Analysis of necessary conditions for learning performance *(Necessity analysis)*

	Consistency	Coverage
Task-technology fit	0.997	0.645
~ Task-technology fit	0.068	0.807
Technology-induced engagement	0.895	0.779
~ Technology-induced engagement	0.202	0.419
Technology-induced motivation	0.943	0.644
~ Technology-induced motivation	0.144	0.870
Gender	0.467	0.656
~ Gender	0.533	0.581
Residential location	0.578	0.631
~ Residential location	0.422	0.591

Necessary condition threshold (Consistency > 0.90)

Table 4 Causal Configurations for Achieving High Learning Performances *(Sufficiency Analysis)*

Configurations	RC	UC	CON
S1: *f*(TaskTechnologyFit * TI-Engagement * TI-Motivation * Gender)	0.39	0.09	0.95
S2: *f*(TaskTechnologyFit *TI-Engagement *TI-Motivation * Residential-Location)	0.54	0.25	0.94
S3: *f*(TaskTechnologyFit * ~ TI-Engagement * ~ TI-Motivation * Gender * ~ Residential-Location)	0.07	0.06	1.0
Solution consistency	*0.95*		
Solution coverage	*0.70*		

* Interaction between conditions, ~ Low score*; RC* Raw coverage*; UC* Unique coverage*; CON* Consistency

5.3 Necessity analysis

The second step of fsQCA analysis is the test for necessity. Necessity means that a condition is a superset of the outcome. For a condition to be necessary, its consistency score should exceed 0.90 threshold. Consistency is the degree to which the cases in the sample that share a causal condition or configuration agree in displaying the focal outcome (Ragin, 2009). In Table 3 all the causal conditions and their negated values (~) are tested for necessity. The results in Table 3 show that TTF and TIM are necessary conditions for achieving high student learning performance.

5.4 Sufficiency analysis

As a next step, fuzzy set analysis for sufficient conditions leading to high student learning performance was carried out. Previously, Table 3 indicates the existence of two possible necessary conditions for achieving high student learning performance that are shared across the three configurations, namely, TTF and TIM. In Table 4, three causal configurations can be considered empirically important with an overall solution (consistency = 0.95) and (coverage = 0.70). The configurations are combinations of conditions that are sufficient, and no single condition is sufficient all by itself to account for high learning performance. According to Ragin (2009), coverage scores can be used to assess empirical importance of combination of causal conditions. Simply, empirical importance is the extent by which an observed outcome is explained by either a specific causal condition or a combination of causal conditions.

Solution 1 Configuration 1 shows that high task-technology fit, high technology-induced engagement, high technology-induced motivation and being female is a sufficient configuration for achieving high student learning performance (Consistency = 0.95) and (coverage = 0.39). This could be interpreted as, the presence of task-technology fit, technology-induced engagement and motivation are likely to predict high learning performance for female students compared to male.

Solution 2 Configuration 2 shows that high task-technology fit, high technology-induced engagement, high technology-induced motivation for students living in urban areas are sufficient configurations for achieving high student learning performance (Consistency = 0.94) and (coverage = 0.54). This could be interpreted as, the presence of task-technology fit, technology-induced engagement and motivation are likely to predict high learning performance for students living in urban areas (i.e., metropolis, large cities) compared to those living in rural areas.

Solution 3 Configuration 3 shows that high task-technology fit, low technology-induced engagement and low technology-induced motivations for female students living in rural areas are sufficient configurations for achieving high student learning performance (Consistency = 1.0) and (coverage = 0.07). This could be interpreted as, regardless of technology-induced engagement and motivation, task-technology fit is likely to predict high learning performance for female students living in rural areas (i.e., villages, towns, and small settlements).

6 Discussion

Past empirical evidence documented a causal link between TTF (Isaac et al., 2019; Lin, 2012), TIE (Garcia-Cabot et al., 2020; Sun, 2014) and TIM (Rashid & Asghar, 2016; Yüce et al., 2019) with learning performance individually and also employed net effects approach. Reports by OECD (2018), delineate the presence of gendered-bias as the root of failures and learning outcomes. And rural areas have been shown to mostly have structural disadvantages, another root of failures and learning outcomes (The World Bank, 2020). The literature is devoid of equifinal classifications of the above said factors or conditions on how they determine learning performance. Equifinality refers to the idea that there are multiple pathways to a given outcome. To bridge the research-practice gap, this study investigated the connections between TTF, TIE, TIM, gender, residential location and learning performance during

Covid-19 pandemic based on dyadic data collected from faculty members and students using fsQCA analysis. The outcomes of this study are four folds:

The first finding is the necessity of TTF and TIM for individual learning performance. This is in line with the claims of Kanfer and Ackerman (1989) that "motivation and cognitive abilities represent two basic determinants of learning and work performance" (p. 657). In order to satisfy the needs to enhance student motivation faculty members should know that different motivational strategies are needed since students at different stages of their college careers have different concerns (Rizkallah & Seitz, 2017). Moreover, quite a number of the reviewed literature contribute to the task-technology fit and learning and individual performance connections (Cane & McCarthy, 2009; Isaac et al., 2019; Lee & Lehto, 2013; Lin, 2012; Yüce et al., 2019).

Secondly, *Solution 1* offers an interesting snapshot on how learning outcomes can be attained. TTF, TIE, and TIM emerge as sufficient conditions by which female students attain high learning performance. Past work has linked the aforementioned conditions using the net effect approach, contrary to existing research, this paper employed a complex causal approach to explain how these conditions work together as a causal recipe in causing learning performance. This paper contends that students' learning performance is largely shaped by their TTF, TIE and TIM; thus, this paper complements existing findings.

Solution 2 delineates that TTF, TIE and TIM are sufficient conditions by which students living in urban areas (i.e., metropolis) attain high learning performance. The present configuration unveils the hidden structural disadvantage faced by students in rural areas, as students in urban areas are more likely to perform well and succeed if they possess high TTF, TIE and TIM. Unlike past research that focuses on the effects of residential location on learning performance (Bacher-Hicks et al., 2020; Clark et al., 2020; Iivari et al., 2020; Song et al., 2020), this paper extends our understanding on how students' settlement or residential location shapes their learning performance by unveiling the interaction with factors such as TTF, TIE and TIM. Simply, students in metropolis residentials such as large cities are performing well academically through high engagement, motivations and technology fit, we suspect that the availability of resources, opportunities, social influence and competitions in the large cities is one of the driving forces. In essence, this paper contends that learning performance should not be evaluated based on students' residential location only, rather a combination of TTF, TIE and TIM as well as residential location.

Solution 3 delineates that TTF is a sufficient condition by which female students living in rural areas attain high learning performance irrespective of/low TIE and TIM. Past work acknowledged that the pandemic has raised a new question about the "Haves and Have Nots" with respect to socio-economic variations of remote rural and urban affluent students (Mishraa et al., 2020). This paper has provided empirical answers to these questions. Our finding is groundbreaking as it reveals the social, cultural, and economic development in the country. Although steps were taken in the last decades by the governments to improve and provide universal education for everyone. Still, there are rural settlements such as small towns and villages that usually do not have the necessary digital infrastructure (e.g., weak network connections and signals for mobile connections). Also, women and girls are usually in an unprivileged position (e.g., early marriage, household chaos, farm works etc.). Building on this line of reasoning, female students from rural areas are largely demotivated and are typically disengaged by technology. However, despite the disengagement and demotivation, female students with high TTF appear to exhibit high learning performance. If efforts are taken, the comatose human capital in rural areas will resurrect and subsequently fill brain drains experienced in the Turkish labor market.

All in all, the results enlightened the differentiation of gender and settlement in developing countries in the context of a digital environment. The digital gender divide is not only a local issue but a global one. Reimers and Schleicher (2020) assessed the situation of OECD countries regarding the effect of the pandemic on education. The report shows that students in OECD countries, especially in rural areas, have difficulties accessing computers and the Internet due to poor digital infrastructure. Saniye Gülser Corat, who is the Director of the Division of Gender Equality in UNESCO suggests "Together we can crack the code, to ensure women and girls, including those in rural settings, have equal opportunities to contribute to and benefit from a more inclusive, equitable and sustainable world." (UNESCO, 2018).

6.1 Implications for administrators in higher educational institutions

The study unveils numerous implications for practitioners and administrators in higher educational institutions. Shenglin et al. (2017) suggests that since technology is dynamic, so education should also be dynamic and stay ahead. The importance of TTF has never been this much important; on the other hand, pressing issues such as digital divide and gender-based digital divide are now exposed. Designing digital-mediated educational tools in a way that will motivate students and also keep them engaged appears to be crucial. This is primarily due to the tendency of disengagement in the virtual classroom. Therefore, professional development initiatives on how faculty members can design, manage, and keep their virtual classes engaged and motivated to equip the next generation of learners with digital knowledge, skill sets, and related competencies are required (Elçi, 2019). Consequently, closing the gender digital divide is more urgent than ever because COVID-19 is increasing society's dependence on technologies for teaching and learning activities. Female students have been shown to outperform their male counterparts in Turkey in terms of academic performance (Dayıoğlu & Türüt-Aşık, 2007). To ensure progression and successful women inclusion in the labor market amid Covid-19, addressing the digital inequalities and gender digital divide appears to be critical.

Educational administrators need to push up and propose policies to the government to increase telecommunication and digital technology infrastructures investment in rural areas. This will not only solve educational problems but may also help combat overpopulation and risk of virus spread in metropolitan areas in the case of a future pandemic. Joint efforts by government, educational institutions, and telecommunications bodies should be made to ensure that the rural and disadvantaged populations have access to network and technology to reduce the impacts of digital inequalities in the COVID-19 context. Mapping out and spotting “digital deserts’’, through proxies such as mobile network coverage, smartphone penetration, or socioeconomic status can be a good step to increase Internet network coverage in Turkey.

It is worthwhile to acknowledge the limitations and deficiencies of online learning platforms and applications. Online learning platforms provide teachers and learners interactive knowledge-building tools to deliver and manage teaching and learning services. On the other hand, access to teaching materials, connection speed, timely transmission of media content, course management, communication, interaction, security, and compatibility are its major pitfalls. Emphasis on improving platform service can enhance timely and convenient access of course content during and after classes. Enhanced interactivity can facilitate learning activities, for instance, students should have the ability to split screens to access content and on the other side interact with the contents (Chen et al., 2020).

Consequently, faculty members require huge theatrical skills (Mishraa, 2020) and digitized assessment skills (Adeshola & Abubakar, 2020) to enhance the flow of learning activities. Besides, there is a limitation for disciplines, for instance, teaching medical, mechanical, civil, and industrial engineering students online can be challenging (Sahi et al., 2020). All in all, online teaching platforms reduce class interaction and peer-to-peer exchange, the elimination of social cues and body language makes learning more difficult (Abubakar & Adeshola, 2019; Seçkin et al., 2020). Inadequate proctoring features can result in extremely high grades and superficial outliers that would otherwise not exist. Distraction is inevitable, and the loss of optimal attention can prevent efficient information sharing on the instructor side and information absorption on the student side.

In the past faculty development centers were mostly overlooked (Elçi, 2019). So, faculty development during and in the post pandemic era justified the words of Bruce Lee (1940–1973) “If you want to learn to swim jump into the water. On dry land no frame of mind is ever going to help you”. Our paper is musing for reconfiguration of faculty development in times of crisis, that is, *Online Faculty Development Programmes* where faculty members are expected to unlearn, learn, relearn, and engage in interactive teaching and learning activities. Seminars and workshops organized either in the institutional capacity or with the help of experts from other institutions can help faculty members. Mentoring and pairing can help faculty members adjust and update teaching materials content according to students needs and expectations. Our recommendation is that faculty development initiatives should preclude important structural changes in policy and procedure. For instance, training on how faculty members can upgrade their theatrical and virtual presentation skills, and digital assessment skills. Most faculty are not aware of approaches and/or the importance of communication in the virtual realm. Thus, we suggest that faculty development programmes should emphasize the need to maintain open channels of communication and show empathy towards learners’ emotions (Kachra & Ma, 2020). We believe that these approaches could boost student TTF, TIE and TIM, that would be translated into success and greater learning performance.

6.2 Implications for research and theory

The present study contributes to five distinct and isolated literature streams at the heightened stage of Covid-19 pandemic: TTF, TIE, TIM, gender- and location-based digital divides. This paper deepens the literature with the inclusion of gender- and location-based digital divides. Past work mostly linked TTF, TIE and TIM with learning performance (Garcia-Cabot et al., 2020; Isaac et al., 2019; Kangas et al., 2017; Rashid & Asghar, 2016; Yüce et al., 2019). From this vantage point, our findings showed the relevance of gender and location in determining student learning performance, which somehow questions and interrogates the validity of past findings. For instance, Gonzalez et al. (2020) did not find any difference as to student performance, while El Refae et al. (2021) found that female students expressed facing challenges with online learning platforms and activities compared to their male counterparts. Given the inconclusiveness of the literature. The present findings are timely and relevant given the disrupts Covid-19 has caused, the virus has altered several existing findings, theories, and ways of doing things. Our results provide initial insights on how to achieve learning performance. Although, the current research is exploratory, the findings highlight avenues to expand this line of inquiry. This work also extends the task technology fit (TTF) and self-determination theories by integrating the relevance of gender. The key lesson learnt is that future research can deploy a wide array of theories across a broad spectrum of perspectives to explain student performance (e.g., social role theory, cultural dimensions, and others).

6.3 Limitations and future research course

The present work has strengths and limitations, as with all empirical research work. In terms of limitations, *initially* the study garnered and analyzed self-reported data during Covid-19 pandemic which is subject to social desirability bias and psychological distress (MacKenzie & Podsakoff, 2012). *Two*, the study sample size is relatively small, although scholars highlighted that such sample size is sufficient for fsQCA analysis (Greckhamer et al., 2013; Marx, 2010). *Three*, data was obtained from dyads in a single university, this limits our ability to generalize the findings. On the other edge, *one* of the study's strengths is the use of multi-sourced data dyads (faculty member-student). This approach allows for concrete conclusions on causal inference and can reduce the potential threat of common method variance (MacKenzie & Podsakoff, 2012). In terms of strengths, fsQCA approach bypasses the net effects weakness of conventional methods such as regression and offers a managerial-friendly exegesis of the outcomes. Finally, we used a dyadic dataset which increases the validity and reliability of the findings.

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