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A Synergy of Knowledge Management Processes Impacting Organizational Ambidexterity for Pakistani IT Firms

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ABSTRACT

Parallel multiple mediation analysis has received limited attention in Business and Management research, despite its potential to provide deeper insights than simple mediation models. This study applies a parallel multiple mediator approach to examine how predictors shape outcomes through simultaneous mediating pathways. Data were collected from 655 respondents in Pakistan's IT sector using an investigative research design. Findings show that the predictor variable improved the outcome by 57% through the mediating mechanism. The two specific indirect effects under study were significantly different from zero (p < .05), confirming partial mediation among the antecedent and consequent variables. These mediating effects highpoint the contribution made by the individual and combined mediators in single-path and parallel- multiple mediator models. Beyond experimental results, this research paper accentuates the significance of conditional process analysis which incorporates the concept of bootstrapping confidence intervals thereby reinforcing the rigor of mediation research. This study offers practical guidance to researchers and students seeking to explore and apply detailed and sophisticated mediation models within organizational contexts.

Keywords: *Parallel Multiple Mediation Model; Simple Mediation Model; Conditional Process Analysis; Bootstrapping, Confidence Interval.*

INTRODUCTION

Mediation analysis was historically conducted using the causal steps approach (Baron & Kenny, 1986), but more recent scholarship emphasizes conditional process analysis for examining complex models of mediation and moderation (Hayes, 2013, 2018; MacKinnon, Lockwood, Hoffman, & West, 2002; Preacher & Hayes, 2004, 2008). Traditional statistical software such as SPSS and SAS do not generate confidence intervals for products of parameters like indirect paths, which are central to mediation. Conditional process analysis addresses this gap by incorporating bias-corrected bootstrapping with at least 5,000 resamples, producing robust confidence intervals and offering a reliable, simplified method for analyzing mediation and moderation effects (Hayes, 2018; MacKinnon, Fritz, Williams, & Lockwood, 2007; Preacher & Hayes, 2008).

The PROCESS method surpasses both the Sobel test and normal theory approaches. The latter assume normality of the indirect effect's sampling distribution, an assumption consistently shown to be inaccurate (Craig, 1936; Bollen & Stine, 1990; Hayes, 2013, 2018; Stone & Sobel, 1990). Moreover, the Sobel test demonstrates lower statistical power and less precise confidence intervals (Hayes & Scharkow, 2013; MacKinnon, Lockwood, & Williams, 2004). In contrast, PROCESS with bootstrapping yields more powerful and reliable confidence intervals. Compared to the causal steps framework (Baron & Kenny, 1986), conditional process analysis is also more rigorous, as it quantifies indirect effects directly rather than inferring them solely from the significance of paths ‘a’ and ‘b’ (Hadi et al., 2016; Fritz & MacKinnon, 2007; MacKinnon et al., 2002).

Beyond efficiency, conditional process analysis enhances accuracy by reducing commands, improving Type I error control, and enabling the comparison of “specific indirect effects” across multiple mediators in parallel models (Hayes, 2018). Bootstrapping further refines analysis by empirically estimating the sampling distribution of indirect effects to construct confidence intervals for indirect, direct, and total effects. Unlike normal theory approaches, it does not assume distributional normality, making it particularly effective for skewed data. For more details on bootstrapping, see Mooney, Mooney, Mooney, & Duval (1993), Lunneborg (2001), Parsonage, Pfannkuch, Wild, & Aloisio (2016), and Wood (2005).

Despite its methodological advantages, parallel mediation remains underutilized in business and management research. To illustrate its application, this study draws on knowledge management processes -m1/KMP with knowledge application & knowledge transfer as its components (Donate & Pablo, 2015), as mediators. The paper concludes with practical recommendations for employing parallel mediation procedures, which can significantly strengthen methodological rigor and theoretical contributions in business and management studies.

Simple and Parallel Multiple Models of Mediators.

Model four of conditional Process analysis, is a statistical method used to measure how forerunner variable ‘x’ influences consequent variable ‘y’ through mediating variable ‘m’. **“**Simple mediator model” only enable researcher to consider one arbitrating mechanism. However, for current study mediator is composed of two component intermediaries and thereby such instances, require that “simple mediator model” approach check the mediating influence of combined mediator, while “parallel multiple mediator model” check the mediating influence of other two component mediators (Hayes, 2018). This permits determination of relative strengths of the mediators. Parallel multiple mediator model has flexibility to appraise more than two mediators, and even as many as seven mediators in the same model simultaneously (Hayes, 2018).

Statistical Equations for Simple Mediator model.

Mediation analyses is a statistical method used to assess ‘how’ causal antecedent variable ‘x’ influences consequent variable ‘y’ through an arbitrating variable ‘m’. Simple mediation model run in PROCESS macro can be summed up in the following equations:

$$\mathbf{m=i+a.x+e\ldots\ldots.\ eq1;}$$

$$\mathbf{y=i+\ c^{/}x+b.m+e\ldots\ldots eq2;}$$

$$\mathbf{y=i+c.x+e\ldots.\ eq3}$$

where i’s are regression constants while **a, b, c, c**$^{/}$ are regression coefficients.

"Direct effect" is pathway that leads from 'x' to 'y' without intervention of 'm'. "Indirect effect" is wherein 'x' first cause 'm', which consequently affects 'y'. Referring to eq2, $\mathbf{c}^{/}$ estimates the "direct effect" of 'x' on 'y'. A general understanding of "direct effect" is that two cases that vary by one unit on 'x' but are equal on 'm', are projected to vary by $c^{/}$ units on 'y'.

The "indirect effect" of x on y is represented by product of paths 'a' and 'b'. Path 'a' measure how much two cases that differ by one unit on 'x' are estimated to differ on 'm'. Path 'b' measure how much 2 cases that differ by one unit on m but that are equal on 'x' are projected to differ by 'b' units on 'y' (eq1). The "indirect effect" of 'x' on 'y' through 'm' is the product of 'a' and 'b'(eq2). Path 'ab' shows that 2 cases which vary by one unit are projected to differ by 'ab' units on 'y' because of the impact of 'x' through 'm'.

The "total effect" on 'x' is represented as c (eq3) which computes how much 2 cases that vary by 1 unit on 'x' are estimated to vary on 'y'. c path can also be calculated as $\mathbf{c= c^{/}+ ab.}$

The ratio of "indirect effect" to "total effect" is "effect size measure", often viewed as proportion of "total effect" that is interceded by mediator. It can be measured through formula P_m=ab/c. The closer P_m is to one the more the effect of, 'x' on 'y', is due to the indirect procedure through intervening variable. Secondly, Fairchild, Mackinnon, Taborga & Taylor (2009) presented the concept of measurement of effect size by understanding and relating the variance explained by "indirect effects" with other variance effects in the model (Hayes, 2009).

The Case of Parallel Multiple Mediator Model Statistical Equations.

Parallel multiple mediator model" with two enabling variables (m1 and m2), and AOX as outcome variable is incorporated. The relationships of parallel multiple models can be expressed in the following equations:

$m1=i\ of_{\ m1}+a_1x+e\ldots\ldots\ldots$ *Eq1*

$m2=i\ of_{\ m2}+a_2\,x+e\ldots\ldots\ldots$ *Eq2*

$y=i\ of_{\ y}+\ c^{/}x\ +b_1\,m_1\ +b_2\,m_2+\ e\ldots\ldots\ldots.$ *Eq3*

$y=i\ of_{\ y}+c\ x+e\ldots\ldots\ldots\ldots\ldots$ *Eq4*

In equations 1, 2, a_1, a_2, guess the quantity by which 2 cases which vary by one unit on 'x' are projected to vary on m_1, m2, respectively. In equation 4 b_1, estimate the quantity by which 2 cases which vary by one unit on m_1 differ on y holding m_2 constant. $c^{/}$ estimates the quantity by which 2 cases which vary by one unit on 'x' differ on 'y' holding m_1, m_2 constant. In this model $\mathbf{c}^{/}$ is direct from x to y, without passing through any facilitator. Each of the "indirect paths", pass through each of the mediator, and are referred to as "specific indirect effects". Thus, a model with 2 mediators has two "specific indirect effects" through m_1 (x—m1—y); m_2(x—m_2—y). The first of these paths is the effect of 'x' on 'm', titled as path 'a' and the second is the path from m to y, titled as path 'b'. Thus, a_1b_1 is the "specific indirect effect" of 'x' on 'y' through m_1; a_2b_2 is the "specific indirect effect" of 'x' on 'y' through m_2. "Total effect" of 'x' on 'y' or Path c is the effect of 'x' on 'y' and can also be expressed as $\mathbf{c= c^{/} + a_1b_1+a_2b_2}$. The ease and utility of

Process lay in its ability to greatly simplify the estimation process by conducting all regression relationships in one command while also generating additional statistics and inferential tests like estimating “standard errors, significance statistics, and bootstrap confidence intervals” for “total and specific indirect effects”.

Conceptual Framework and Hypothesis Building

Open Systems idea has determined its manner in few areas and fields. It is tested with the aid of using the idea that any tool can be characterised as a set of inter-associated things: inputs, techniques, outputs (Boulding, 1956; Checkland, 1994; Checkland and Scholes, 1999; Jhonson, Kast and Rosenzweig, 1964; Robbins and Coulter, 2018; Rothwell, and Kazanas, 2011). The inputs may be uncooked materials, human assets or truth and capital approximately the antecedent variables. Operations are sports that charges are uploaded directly to inputs. The entire merchandize and offerings are outputs. This perception is embraced into the high-tech look at as a way to live to tell the tale the antecedent variables turning into a translucent input, the mediating variables withinside the shape of the operations or methods and organizational very last effects variable turning into the output of the present day day take a look at.

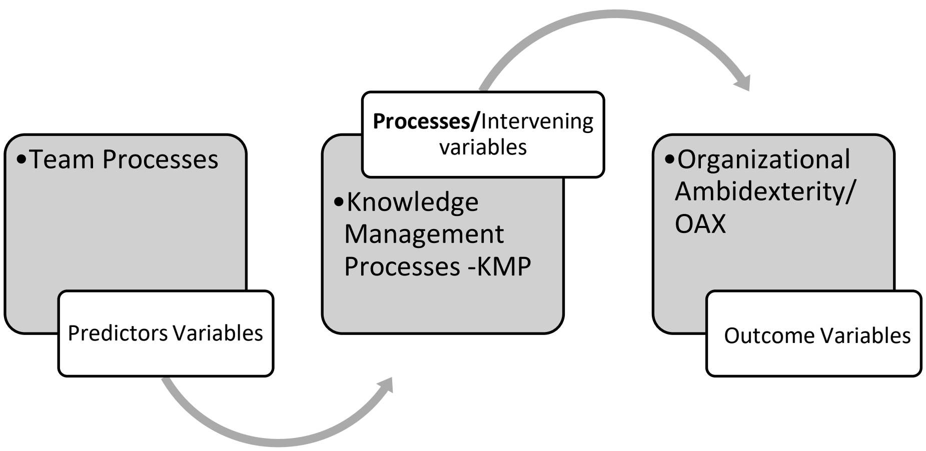


Figure 1: Conceptual Model

Fig 1 indicates the rules of the studies version that has been used withinside the contemporary study. The enter or antecedents were taken into consideration because the TMP/Team methods and mediating strategies had been taken into consideration as KMP/Knowledge control approaches of 3 theoretical paperwork while the output or organizational final results variable has been taken as Organizational ambidexterity/OAX (Mahmood, Qureshi, and Hadi, 2019). Team methods (Sumner and Slattery, 2010) embody comprising sports involving: settlement of objectives; green incorporation of resources, with the aid of using the crew participants and their leader; instituting elements of trust; group leadership; powerful communications; and possible choice making amongst crew participants. Knowledge control techniques/KMP (Mahmood, Qureshi, and Hadi, 2019; Mahmood and Hadi, 2020) is taken into consideration to be a mixed mediator that consists of m1/KMP (Donate & Pablo, 2015). Dependent variable Organizational Outcome /Organizational Ambidexterity=Exploratory innovation and Exploitative innovation. Exploitative improvements are incremental improvements aimed toward fulfilling the wishes of present clients, current markets, current services/products, present distribution channels etc. Explanatory improvements are new improvements geared toward gratifying the wishes of recent clients and markets, services/products, distribution channels etc. (Jansen, Van Den Bosch, and Volberda, 2006; Junni, Sarala, Taras, and Tarba, 2013).

Hypotheses:

H1: Team processes positively effect “organizational ambidexterity”. (Path c)

H2: Team processes positively effect “knowledge management processes”. (Path a)

H3: “Knowledge management processes” positively effect “organizational ambidexterity”. (Path ‘b’)

H4: “Knowledge management processes” mediate between team processes and “organizational ambidexterity” (Paths $c^/$ & a*b)

H4a: “Knowledge application/KA/m1” mediate between team processes and “organizational ambidexterity” (Path a^1* b^1)

H4b: “Knowledge transfer/KT/m2” mediate between team processes and “organizational ambidexterity”. (Path a^2* b^2)

Data Collection

Sample size was determined based on the statistical techniques employed for the present study for confirming mediation analysis, Fritz & MacKinnon (2007) recommended that to gain substantial results and effect sizes, at least 500 sample size is required and sample sizes greater than 558 are most favorable. Survey was closed on getting a fair sample size of 655.

Simple Mediator Model Implementation

This section elaborates a practical example for simple mediator model.

Simple Mediation Model for TMP, KMP, & AOX

In this section, mediation hypotheses H1-H4 are being tested with Process/ Mediation with model 4 of conditional process analysis (Hayes, 2013 & 2018). H1 states that TMP positively influences AOX and represents path ‘c’ of mediation model; H2 states that TMP positively influences KMP and represents path ‘a’ of mediation model and H3 states that KMP positively influences AOX and represents path ‘b’ of mediation model while H4 states that KMP mediates relationship between TMP and AOX and represents path $\mathbf{c}^/$ of mediation model.

Figure 2 shows the results of mediation with bootstrapping. Results show that none of the confidence intervals related with paths ‘a’, ‘b’, ‘c’, and ‘$c^/$ have zero in them showing that mediation is a valid result. Tables 1 and 2 review the bootstrapping results with mediation.

Simple Mediation version of estimation and statistical inference above Simple Mediation Model-Team Processes/TMP/Antecedent Knowledge and Learning Processes/KLP/Mediator - Organizational Ambidexterity/AOX/Outcome variable

Referring to Fig 1 TMP/Team Processes influences “knowledge management processes/KMP”, which consequently achieve organizational ambidexterity/AOX. Process output is summarized in Table 1, where a=.5927; b= .4105; c= .4648; $\mathbf{c}^/$=.2371. So, the model in Figure 2 can be expressed as m=1.1+.59x;

y=1.02+.24x+.41m; Total effect or y=1.47+.48x. The "indirect effect ab" =.2371, path 'ab' shows that 2 cases that fluctuate by one unit on x/TMP are appraised to vary by '.2371' units on dependent variable because of mediating influence of the intervening variable. The "indirect effect" is statistically different from zero, as is shown by 95% bootstrap confidence interval (.2323 to .3125).
The "direct effect" of TMP is .2731 on AOX when KLP mediator is controlled. It shows that when two cases that vary by one unit on x/TMP but are equivalent on m/KLP are projected to vary by .2731 units on y/AOX. Direct effect" was statistically different from zero t (652) =7.7, p=.0000 with 95% confidence interval from .2323 to .3125. The "total effect" of TMP on AOX is obtained by adding the "direct and indirect effects". c= .2371+.2433=.4804. "Total effect" counts how much in two situations that vary by one unit on x/TMP are expected to differ by .4648 units on y/AOX. This effect is statistically dissimilar from zero t (603) =16.314, p=.0000 with a 95% confidence interval from .3543 to .4667.

Table 1

Model Coefficients for TMP-KMP-AOX

	CONSEQUENT											
	M (KMP)				Y (AOX)				Y (AOX) Total effect			
independent		coefficient	s.e	p		coefficient	s.e	p		coefficient	s.e	p
x(TMP)	a	.5927	.0351	.0000	c'	.2371	.0308	.0000	c	.4804	.0294	.0000
m(KMP)					b	.4105	.0286	.0000				
Constants	i_m	1.0892	.1130	.0000	i_y	1.0200	.0883	.0000	i_y	1.467	.0947	.0000
	R^2=.30;p<.001; F(1,653)=284.642				R^2=.46; p<.001; F(1,652)=277.6649				R^2=.2896; p<.001; F(1,653)=266.1679			

3 Summarized results--- team processes/TMP/Antecedent—Knowledge Management Processes/ KMP/Mediator--- Organizational Ambidexterity/AOX/Outcome variable)

Referring to Table 2, Firstly, results showed that antecedent/TMP positively influenced outcome variable/OAX (B=4804, t (653) =16.37, p<.001). It was also established that antecedent/TMP positively influenced mediator/KLP (B=.5927, t (653) =20.51, p<.001). Furthermore, the findings supported that mediator/KMP, positively influenced outcome/OAX (B=.4105, t (652) =16.87, p<.001). Since both paths 'a' and 'b' were much significant, mediation investigation was run using the "bootstrapping method with bias-corrected confidence estimates (Mc Kinnon, Lockwood & William, 2004; Preacher & Hayes, 2018)". Results of the mediation analysis established the interceding role of mediator/KMP in association between outcome/OAX and antecedent/TMP (a*b=.2725, C1=.2039 to .2837). More so, results, showed that the "direct effect" of antecedent/TMP on output/OAX lowered but persisted to be significant (B=.23, t (652) =7.7, p=.0000) when adjusting for mediator/KLP, therefore indicating partial mediation. Whilst analyzing for "effect size 1 ab_{cs}" CI=.2323 to .3125, thus "completely standardized indirect effect" of 'x' on 'y' does not have a zero in its confidence interval. Whilst determining effect size 2, percentage of intervention is $P_{m=}$ 57%. This implies that mediating variable explains for 57% of "total effect". Secondly small discrepancy in AOX is explained by TMP (R^2=.20) whereas the collectively both antecedent and mediating variable yielded greater variation (R^2=.46).

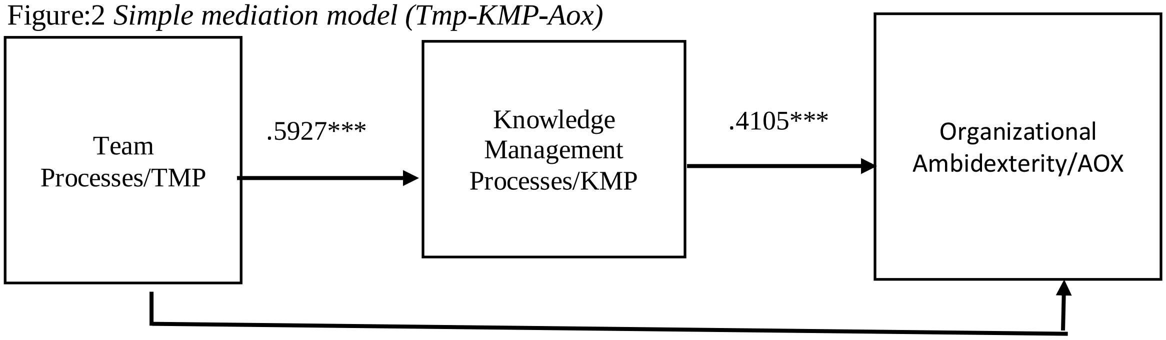
Thus H1-H4 are all confirmed.

Table: 2

Coefficients for TMP-KMP-AOX

Testing Paths	B	SE(B)	95% CI
Path c: Dependent Variable=OAX			
R^2=.28, F (1, 653) = 266.16, p=.000			
Independent V=TMP	.4804	.0294	.4225 to .5382
Path a: Dep V=KLP			
R^2=.30, F (1,653) =284.66 p=.0000			
Indep V=TMP	.5927	.0351	.5237 to .6617
Path b & c^{-} DepV=OAX			
R^2=.46, F (2,652) =277.65, p=.000			
Indep V =TMP (c^{-})	.2371	.0308	.1766 to .2975
Indep V =KLP (b)	.4105	.0268	.3543 to .4667
Total=(a*b)	.2725	.0204	.2323 to .3125

Figure:2 *Simple mediation model (Tmp-KMP-Aox)*



.23*** (.48***)
Note: *** p<.001
Simple Mediation Model TMP-KMP-AOX

Table 3 (appendix) and Fig 3, show parallel multiple model with 2 mediators (m1/KA, m2/KT) and TMP and AOX as independent and dependent variables are described as follows: a_1=.5311; a_2=.5285; $\mathbf{c}^{/}$=.2661; c=.5381; b_1=.1809; $b_{2=}$.3329.

The "indirect effects" are:

$m1=i\ of_{\ m1}+a_1x+e$……… *Eq1;* KA/m_1=3.1+.5311x

$m2=i\ of_{\ m2}+a_2\,x+e$……… *Eq2;* KT/$m_{2=}$5.6+.5285x

The "direct and indirect effects" are $y=i\ of_{\ y}+\ c^{/}x\ +b_1\ m_1\ +b_2\ m_2\ +\ e$…*Eq3;* y=1.01+.2661x+.1809m_1+.3329m_2

"Total effect model" is $y=i\ of_{\ y}+c\ x+e$…………… *Eq4;* or y=1.54+=.5381x

Little variance in KA/m_1, KT/m_2 is explained by 'x' (R^2=.22, .28 respectively) whereas the combined effect of independent variable and all 3 mediators has brought a much superior difference R^2=.48. A "specific indirect effect" is understood as the quantity by which two cases differing by one unit on independent variable are projected to vary on dependent variable through intervening variable independent of other mediators.

The "specific indirect effects" of TMP through m1/KA on AOX is a_1b_1 =.0961. Two cases that vary by one unit on x/TMP are appraised to differ by .0961 units on y/AOX through institution of m1/KA. A "second indirect effect" of TMP on AOX is routed through m2/KT, estimated as a_2b_2=.1759. Two cases that vary by one unit on x/TMP are projected to vary by .1759 units on y/AOX through institution of m2/KCP. The "total indirect effect" of x on y is sum of all mediating paths. This is =.2661+.0961 +.1759=.5381. Thus 2 cases that vary by one unit on x/TMP when mediated through combined effects of 3 mediators bring about .5381 units change in y/AOX. The "direct effect" $\mathbf{c}^{/}$=.2661 quantifies the effect of the operation of x/TMP on y/AOX independent of the effect of the proposed mediators.

The "total effect"

$c=\mathbf{c}^{/}+a_1b_1+a_2b_2$

c=.2661+.0961 +.1759=.5381

Statistical Inference for the Paths

Referring to table 3 (appendix) statistical inference for paths as shown in fig 3 is being shown. The "Direct Effect": $\mathbf{c}^{/}$=.2661, t (653) =16.3, p=.0001. Thus, path $c^{/}$ is significant because with 95% confidence interval (.0701 to .2059) which indicates the influence of TMP on AOX when all 3 mediators are controlled is significant. "Total effect": is denoted by c in y=i+cx. c is the coefficient of x and is c=.4648; p=.0000 with a 95% confidence interval (.4225 to.5382).

"Specific Indirect Effects": With several 5000 bootstraps estimates of each specific indirect effect, end points of the confidence interval are calculated. If 0 is outside of confidence interval of path 'ab' then path 'ab' is declared different from 0 with confidence, whereas if confidence interval contains 0 then it leads to conclusion that there is insufficient evidence that 'x' effects 'y' through 'm'. Bootstrap confidence interval supports the claim with 95% confidence that antecedent/TMP influences outcome/AOX indirectly through 2 mediators m1/KA (.0428 to.1319); m2/KCP (.1091 to .2053) as all two confidence intervals are above 0. Thus H4a, H4b are all accepted

Insert table 3 given in appendix 1 here.

Pairwise Comparisons between Specific Indirect Effects

In this part there is a discussion on whether, the a1b1 is stronger or a2b2 or the specific indirect effects of the proposed mediators are entirely different. When the confidence interval of the contrasts, is non zero, then it provides the grant that the two of the indirect effects or mediating mechanisms are statistically different between them. Where a confidence interval is a two-sided interval in which the value is zero one would say that the two indirect effects or respective intervening mechanisms are not statistically different. On the approximation of the power of which a specific indirect effect and which mediator is the superior, point estimates are obtained of both specific indirect effects. The larger of the two in absolute value is better in effect than the other.

Considering contrast1/C1= a1b1- a2b2, (-.0713) zero which in confidence interval (-.1526 to.0140) = 0 hence they are not significantly different.

Parallel Multiple media tor model Total indirect effect: In parallel multiple media tor model the total indirect effect is the summation of specific indirect effect. Interaction between 2 mediating variables shown as the total indirect effect of independent variable on dependent variable is .5513x.1570=.0858+.1570=.2428.

Secondly we can say we have 95 percent confidence that there is an indirect effect between the precursor variable and the outcome variable with 2 intermediates, is in the range of.2040 to.2834. Such a confidence interval is larger than zero, helpful in the fact that the two predicting variables can mediate the outcome of independent variable to the dependent variable collaboratively.

Table: 4

Point Estimates and Confidence intervals for TMP—KMP—AOX

mediation pathway	point estimate	se	bc 95% c.i	
			lower	upper
Indirect Effects				
Total	.2428	.0201	.2040	.2834
KA	.0858	.0227	.0428	.1319
KT	.1570	.0243	.1091	.2053

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Contrasts				
C1=KA-KT	-.0713	.0425	-.1526	.0140

Figure: 3

Parallel Multiple Mediator Model TMP-m1, m2, -AOX

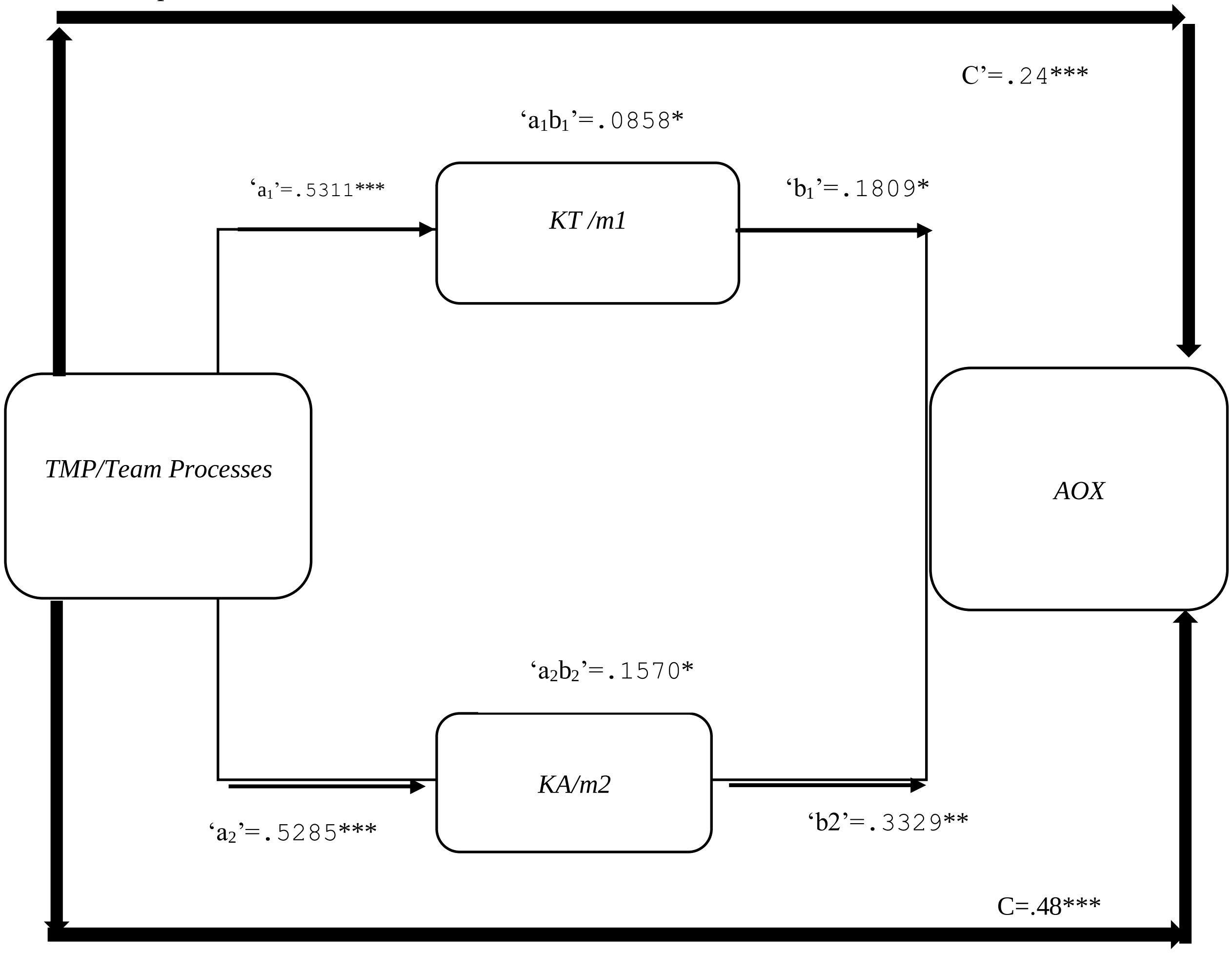

Fig 3: Parallel Multiple Mediator Model. Note. $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$.

CONCLUSION AND LIMITATIONS

This study focused exclusively on simple and parallel multiple mediator models. To strengthen validity, future research should also confirm item loadings on factors using exploratory factor analysis and establish reliability and validity through confirmatory factor analysis (Hair et al., 2009; Mahmood, Qureshi, & Hadi, 2019; Mahmood & Hadi, 2020; Mahmood et al., 2024). Following Hayes' (2018) recommendations, the parallel multiple mediator model was adopted as a complementary approach to the simple mediation model. The simple mediation model tests whether a single mediator transmits the effect of an antecedent to a consequent variable, thereby clarifying the underlying process. However, when multiple mediators are involved—or when a single mediator consists of several distinct components—the parallel multiple mediator model is more appropriate, as it enables comparison of the relative strengths of mediating effects. In this study, extension of Model 4 allowed us to identify the individual mediating roles of each component within the combined mediator and determine which had the strongest influence. Beyond these models, conditional process analysis also provides a range of mediation and moderation designs, enhanced by bootstrapping confidence intervals to ensure reliable estimates.

In addition, the study incorporated open systems theory (Boulding, 1956; Checkland, 1994; Checkland & Scholes, 1999; Johnson et al., 1964; Robbins & Coulter, 2018; Rothwell & Kazanas, 2011) to understand input–output processes within organizational systems, validated here through Model 4 of conditional process analysis. Accordingly, we recommend the use of simple and parallel multiple mediation models within conditional process analysis for future investigations of intervening mechanisms between independent and dependent variables.

Most importantly, this study confirmed the partial mediating role of knowledge management processes in enabling ambidextrous innovation under team processes in Pakistan's knowledge-based IT sector. It is imperative that future research systematically examines diverse configurations of knowledge management, knowledge creation, and learning—particularly intuitive processes (Mahmood & Hadi, 2020)—to establish their role as indispensable enablers of organizational ambidexterity. Such investigations must account for varying antecedents to reveal how these processes dynamically interact to orchestrate ambidextrous outcomes (Mahmood, Qureshi, & Hadi, 2019; Mahmood et al., 2024). The findings of these prior researches align with seminal researches that emphasized examining mediating processes underpinning ambidextrously designed innovations in the presence of diverse antecedents (Birkinshaw & Gupta, 2013; Junni et al., 2013; O'Reilly & Tushman, 2011, 2013). Future studies are encouraged to test different configurations of knowledge and learning processes for ambidextrous innovation across other sectors and countries, taking into account contextual variations to further validate and extend the present study's conclusions.

BIBLIOGRAPHY

Baron, R. M., & Kenny, D. A. (1986). The moderator–mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. *Journal of personality and social psychology*, *51*(6), 1173.

Birkinshaw, J., & Gupta, K. (2013). Clarifying the distinctive contribution of ambidexterity to the field of organization studies. *The Academy of Management Perspectives*, *27*(4), 287-298.

Bollen, K. A., & Stine, R. (1990). Direct and indirect effects: Classical and bootstrap estimates of variability. *Sociological methodology*, 115-140.

Boulding, K. E. (1956). General systems theory—the skeleton of science. *Management science*, *2*(3), 197-208.

Checkland, P. (1994). Systems theory and management thinking. *American Behavioral Scientist*, *38*(1), 75-91.

Checkland, P., & Scholes, J. (1999). *Soft systems methodology: a 30-year retrospective* (pp. 330-pages). Chichester: John Wiley.

Craig, C. C. (1936). On the frequency function of xy. *The Annals of Mathematical Statistics*, *7*(1), 1-15.

Crossan, M. M., Lane, H. W., & White, R. E. (1999). An organizational learning framework: From intuition to institution. *Academy of management review*, *24*(3), 522-537.

Donate, M. J., & de Pablo, J. D. S. (2015). The role of knowledge-oriented leadership in knowledge management practices and innovation. *Journal of Business Research*, *68*(2), 360-370.

Fairchild, A. J., MacKinnon, D. P., Taborga, M. P., & Taylor, A. B. (2009). R 2 effect-size measures for mediation analysis. *Behavior research methods*, *41*(2), 486-498.

Fritz, M. S., & MacKinnon, D. P. (2007). Required sample size to detect the mediated effect. *Psychological science*, *18*(3), 233-239.

Jansen, J. J., Van Den Bosch, F. A., & Volberda, H. W. (2006). Exploratory innovation, exploitative innovation, and performance: Effects of organizational antecedents and environmental moderators. *Management science*, *52*(11), 1661-1674.

Johnson, R. A., Kast, F. E., & Rosenzweig, J. E. (1964). Systems theory and management. *Management Science*, *10*(2), 367-384.

Junni, P., Sarala, R. M., Taras, V., & Tarba, S. Y. (2013). Organizational ambidexterity and performance: A meta-analysis. *The Academy of Management Perspectives*, *27*(4), 299-312.

Hair, J. F., Black, W. C., Babin, B. J., Anderson, R. E., & Tatham, R. L. (2009). *Multivariate data analysis*. Upper Saddle River, NJ: Prentice hall.

Hayes, A. F. (2009). Beyond Baron and Kenny: Statistical mediation analysis in the new millennium. *Communication monographs*, *76*(4), 408-420.

Hayes, A.F. (2013). Introduction to mediation, moderation, and conditional process analysis: A regression-based approach. New York , NY: Guilford Press.

Hayes, AF (2018). Introduction to mediation, moderation, and conditional process analysis: A regression-based approach. New York , NY: Guilford Press.

Hayes, A. F., & Scharkow, M. (2013). The relative trustworthiness of inferential tests of the indirect effect in statistical mediation analysis: Does method really matter?. *Psychological science*, *24*(10), 1918-1927.

Lee, H., & Choi, B. (2003). Knowledge management enablers, processes, and organizational performance: An integrative view and empirical examination. *Journal of management information systems*, *20*(1), 179-228.

Lunneborg, C. E. (2001). Random assignment of available cases: Bootstrap standard errors and confidence intervals. *Psychological methods*, *6*(4), 402.

MacKinnon, D. P., Fritz, M. S., Williams, J., & Lockwood, C. M. (2007). Distribution of the product confidence limits for the indirect effect: Program PRODCLIN. *Behavior research methods*, *39*(3), 384-389.

MacKinnon, D. P., Lockwood, C. M., Hoffman, J. M., West, S. G., & Sheets, V. (2002). A comparison of methods to test mediation and other intervening variable effects. *Psychological methods*, *7*(1), 83.

MacKinnon, D. P., Lockwood, C. M., & Williams, J. (2004). Confidence limits for the indirect effect: Distribution of the product and resampling methods. *Multivariate behavioral research*, *39*(1), 99-128.

Mahmood, N., Qureshi, M. A., & Hadi, ul. N., (2019). Industry Cluster Resources Impacting Dual innovations in Pakistan's IT Sector: Mediating Effect of Knowledge & Learning Processes. *City University Research Journal*, *9*(1), 144-163.

Mahmood, N., & Hadi, ul. N., (2020). Intuition, Knowledge Management, & SECI in Global Perspectives and Iqbal’s thought: A Prospect for Innovative Organizational Outcomes. *The Iqbal Review*.

Mahmood, N., Hadi, N. U., & Talha, M. (2024). Simple mediation analysis: the complementing role of parallel multiple mediation approach via process analysis. In R. K. Hamdan & A. Buallay (Eds.), Artificial Intelligence (AI) and Customer Social Responsibility (CSR) (pp. 479–493). Springer Nature Switzerland.

Mooney, C. F., Mooney, C. L., Mooney, C. Z., Duval, R. D., & Duvall, R. (1993). *Bootstrapping: A nonparametric approach to statistical inference* (No. 95). Sage.

Nonaka, I., Byosiere, P., Borucki, C. C., & Konno, N. (1994). Organizational knowledge creation theory: a first comprehensive test. *International Business Review*, *3*(4), 337-351.

O'Reilly, C. A., & Tushman, M. L. (2011). Organizational ambidexterity in action: How managers explore and exploit. *California Management Review*, *53*(4), 5-22.

O'Reilly, C. A., & Tushman, M. L. (2013). Organizational ambidexterity: Past, present, and future. *The Academy of Management Perspectives*, *27*(4), 324-338.

Parsonage, R., Pfannkuch, M., Wild, C. J., & Aloisio, K. (2016). Bootstrapping confidence intervals. In *The teaching and learning of statistics* (pp. 181-191). Springer, Cham.

Preacher, K. J., & Hayes, A. F. (2008). Asymptotic and resampling strategies for assessing and comparing indirect effects in multiple mediator models. *Behavior research methods*, *40*(3), 879-891.

Preacher, K. J., & Hayes, A. F. (2004). SPSS and SAS procedures for estimating indirect effects in simple mediation models. *Behavior research methods, instruments, & computers*, *36*(4), 717-731.

Robins. S. P., & Coulter. M.K., (2018). Upper Saddle River, NJ : Pearson Prentice Hall.

Rothwell, W. J., & Kazanas, H. C. (2011). *Mastering the instructional design process: A systematic approach*. John Wiley & Sons.

Stone, C. A., & Sobel, M. E. (1990). The robustness of estimates of total indirect effects in covariance structure models estimated by maximum. *Psychometrika*, *55*(2), 337-352.

Sumner, M., & Slattery, D. (2010). The impact of leadership effectiveness and team processes on team performance in construction. *International journal of construction education and research*, *6*(3), 179-201.

Wood, M. (2005). Bootstrapped confidence intervals as an approach to statistical inference. *Organizational Research Methods*, *8*(4), 454-470.

APPENDIX 1

Table.3. Regression coefficients, Standard errors, & Model Summary Information for Parallel Multiple Mediator Model

	M_1(KA)				**M_2(KT)**				**Y(AOX)**				**Y(AOX)**			
Antecedents		**Coef**		**P**		**Coef**		**P**		**Coef**		**P**		**Coef**		**P**
X(TMP)	a_1	.5285		.0000	a_2	.5916		.0000	c'	.2375		.0001	c	.5381		.0000
M_1(KA)									b_1	.0472		.0000				
M_2(KT)									b_2	.0537		.0000				
Constant	I_{m1}	3.0834		.0000	i_{m2}	5.6299		.0000	i_y	1.0193		.0000	i_y	1.4671		.0000
	R^2=.28; F(1,653)=256.6050; p<.001				R^2=.28; F=(1,653)=253.0838; p<.001				R^2=.46; F(1,651)=184.8816 p<.001				R^2=.29; F(1,653)=266.1679;p<.001			