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HOW TO INFER MATHEMATICAL SEQUENTIAL MEDIATION RELATIONSHIPS FROM NETWORK ANALYSIS

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Abstract: *This paper explores the statistical inference of mathematical sequential mediation relationships through network analysis, utilizing JASP for network modeling and SPSS Process Macro (Model 6) for mediation analysis. Sequential mediation analysis is particularly useful when dealing with highly complex theoretical models or when no theoretical model exists, enabling exploratory or confirmatory studies of specific mediation relationships. Network analysis serves as a complementary tool to identify potential pathways and interrelations within variables before applying mediation models. The paper includes an applied example within a study that uses an extended Technology Acceptance Model (TAM) to identify factors promoting TAM adoption among preschool teachers. The methodological implications of combining sequential mediation and network analysis are discussed, offering significant contributions to the behavioral sciences.*

Key words: *sequential mediation; network analysis; SPSS Process Macro; JASP; Technology Acceptance Model (TAM).*

Introduction

In contemporary research, understanding complex relational structures among variables is paramount for advancing theoretical and applied knowledge in psychology and education. Sequential mediation analysis and network analysis are two advanced methodologies that allow for such in-depth investigations. This paper aims to provide a methodological and theoretical framework for mathematically extracting sequential mediation relationships from network analysis results, bridging the gap between exploratory network approaches and confirmatory mediation testing.

Sequential mediation analysis is a robust statistical approach that identifies indirect pathways through which a predictor variable influences an outcome variable via two or more mediators arranged in a specific order. Unlike simple mediation models, sequential mediation allows researchers to explore cascading effects and multi-step mechanisms within a system, providing nuanced insights into how variables interact dynamically (Hayes, 2017). This methodological framework is particularly valuable for uncovering relationships in systems with multiple interacting constructs, such as psychological or educational settings (Shelleby et al., 2014; Caleon et al., 2019; Marici et al., 2024).

Network analysis, on the other hand, visualizes and quantifies the relationships among variables by mapping connections and identifying central nodes within a network. This exploratory method provides a powerful tool for uncovering complex interdependencies and potential mediational pathways in multidimensional datasets. By leveraging metrics such as centrality, clustering coefficients, and community detection, researchers can generate hypotheses about possible sequential mediation relationships that can subsequently be tested using traditional statistical methods (Delcea et al., 2023; Rad, Redeș et al., 2023; Runcan et al., 2023).

The integration of network analysis and sequential mediation offers a unique methodological synergy. Network analysis enables the identification of key mediating variables and potential paths of influence, which can guide the design of sequential mediation models. This combined approach is particularly useful when theoretical guidance is sparse or when the data exhibit high dimensionality, as seen in behavioral sciences and educational research (Rad, Dughi et al., 2020; Rad, Marcu et al., 2024). For example, Dughi et al. (2023) demonstrated the utility of this integration by examining the indirect effects of classroom comfort and faculty support on student grit through network analysis-driven sequential mediation.

A core application of this framework lies in extending the Technology Acceptance Model (TAM) to explore technology adoption behaviors in complex educational environments. TAM, initially developed by Davis (1989), has been widely utilized to explain technology adoption based on constructs such as perceived usefulness and ease of use. Recent extensions of TAM incorporate variables like perceived risk, subjective norms, and hedonic motivations, offering a richer understanding of user behavior in various contexts (Featherman & Fuller, 2003; Altin Gumussoy et al., 2018; Saber Chtourou & Souiden, 2010). By integrating network analysis, researchers can identify interrelations among these constructs, providing a data-driven foundation for sequential mediation models (Rad, Magulod et al., 2022; Scherer et al., 2019).

Methodologically, this paper utilizes JASP for network modeling and SPSS Process Macro (Model 6) for sequential mediation analysis. JASP provides a user-friendly interface for visualizing networks and calculating essential metrics, while SPSS Process Macro allows for rigorous testing of hypothesized mediation pathways. Together, these tools enable the extraction of meaningful insights from large datasets, fostering a deeper understanding of how variables interact in complex systems.

By focusing on the interplay between network analysis and sequential mediation, this paper contributes to the methodological discourse in behavioral sciences. It establishes a replicable framework for analyzing complex relationships, offering practical insights into how sequential mediation relationships can be mathematically inferred from network data. This approach is particularly relevant for exploratory studies in contexts where theoretical models are either underdeveloped or absent, as it allows researchers to generate and test hypotheses grounded in empirical data. The implications of this integrated approach extend to various domains, including psychology, education, and social sciences, where understanding indirect effects is crucial for advancing theoretical and practical knowledge.

Mathematical foundations of network analysis and sequential mediation analysis

The integration of network analysis and sequential mediation analysis represents a significant methodological advancement in psychological and behavioral sciences. These approaches, grounded in graph theory and statistical modeling, respectively, offer complementary tools for uncovering complex relationships within large datasets. Network analysis facilitates hypothesis generation by mapping and quantifying relational structures, while sequential mediation analysis rigorously tests these hypotheses to identify indirect effects and mediator pathways. This section explores the mathematical underpinnings of these methods, focusing on their application to models like the Technology Acceptance Model (TAM).

Network analysis employs graph theory to represent variables as nodes and their interactions as edges, providing both a visual and quantitative understanding of relational structures. Relationships among variables are captured in an adjacency matrix, where each element denotes the presence or strength of the connection between nodes. Several key metrics derived from are instrumental in identifying influential nodes and potential mediators within the network:

- Betweenness centrality - quantifies how often a node lies on the shortest paths between other nodes in the network. Nodes with high betweenness centrality serve as crucial bridges, facilitating interactions and information flow between disconnected parts of the network. In psychological research, such nodes often represent key mediators that connect otherwise isolated variables or groups.

- Closeness centrality - measures how accessible a node is by calculating its average distance to all other nodes in the network. Nodes with high closeness centrality are well-positioned to quickly influence or interact with other nodes, making them influential in spreading information or effects throughout the network. In behavioral studies, these nodes might represent variables that play a central role in initiating or amplifying effects.
- Strength (Weighted Degree Centrality) - captures the overall connectedness of a node by summing the weights of its connections, rather than simply counting the number of connections. Nodes with high strength have strong and robust ties to other variables, indicating their pivotal role in maintaining the structural integrity of the network. In applied contexts, these nodes might signify constructs with substantial direct influence on multiple outcomes.
- Expected influence - expands on strength by accounting for both direct and indirect effects of a node on others. This metric reflects not only how strongly a node is connected to its immediate neighbors but also how it indirectly impacts the broader network. Nodes with high expected influence have the potential to shape the dynamics of the network significantly, making them critical for understanding cascading effects in sequential relationships.

These metrics collectively help identify variables likely to mediate relationships within a network, laying the groundwork for further investigation through sequential mediation analysis.

Sequential mediation analysis extends simple mediation models by examining indirect effects through multiple mediators arranged in a specific order. Sequential mediation models are often estimated using regression-based techniques, such as those implemented in SPSS Process Macro (Model 6), which test the statistical significance of indirect pathways.

This integrated framework has been applied in various studies, including Rad, Redeș, and colleagues' (2023) exploration of teacher cognitive presence, classroom comfort, and student grit. Similarly, integrating TAM constructs with network metrics has revealed significant pathways of technology acceptance (Davis, 1989; Scherer et al., 2019). By combining the exploratory power of network analysis with the confirmatory rigor of sequential mediation analysis, researchers can uncover and validate complex relational dynamics, advancing theoretical and applied research in behavioral sciences.

Case study

This case study examines an extended Technology Acceptance Model (TAM) by integrating additional constructs such as emotional consequences of Zoom fatigue and perceived risk. The TAM framework, initially introduced by Davis (1989), has been widely used to explore user acceptance of technology based on perceived usefulness and perceived ease of use. Extensions of TAM have incorporated variables such as perceived enjoyment, compatibility, and self-efficacy, which enhance its applicability to diverse technological contexts (Marangunić & Granić, 2015; Scherer, Siddiq, & Tondeur, 2019). The inclusion of Zoom fatigue and perceived risk aligns with recent research addressing emotional and cognitive barriers to technology use in educational and professional settings (Fosslien & Duffy, 2020; Riedl, 2022).

Descriptive statistics provide insights into the central tendencies and variability of the constructs measured in the study. Table 1 summarizes the descriptive statistics for the variables included in the extended TAM model.

					95% Confidence Interval Mean				
	Valid	**Missing**	**Mean**	**Std. Error of Mean**	**Upper**	**Lower**	**Std. Deviation**	**Minimum**	**Maximum**
D1_Perceived_usefulness	182	0	2.560	0.084	2.725	2.396	1.129	1.000	5.000
D2_Perceived_ease_of_use	182	0	3.070	0.068	3.204	2.937	0.919	1.000	5.000
D3_Perceived_enjoyment	182	0	3.254	0.077	3.405	3.104	1.035	1.000	5.000
D4_Intention_to_use	182	0	3.170	0.087	3.342	2.999	1.179	1.000	5.000
D5_Actual_use	182	0	2.929	0.086	3.097	2.761	1.156	1.000	5.000
D6_Compatibility	182	0	3.002	0.078	3.154	2.850	1.047	1.000	5.000
D7_Attitude	18	0	2.9	0.0	3.0	2.7	1.11	1.00	5.000

	Valid	Missing	Mean	Std. Error of Mean	95% Confidence Interval Mean Upper	95% Confidence Interval Mean Lower	Std. Deviation	Minimum	Maximum
	2		18	83	80	55	9	0	
D8_Self_effycacy	182	0	3.872	0.064	3.998	3.746	0.869	1.000	5.000
D9_Emotional_consequences_of_Zoom_fatigue	182	0	3.009	0.073	3.152	2.866	0.986	1.000	5.000
D10_Perceiced_risk	182	0	3.526	0.077	3.676	3.376	1.033	1.000	5.000

Table 1. Descriptive Statistics

The Pearson correlation matrix highlights the relationships among variables in the extended TAM model (Table 2). Significant correlations (p < .05) reveal potential pathways and interdependencies between constructs.

Variable	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
1. D1 Perceived usefulness	—									
2. D2 Perceived ease of use	0.523 ***	—								
3. D3 Perceived enjoyment	0.572 ***	0.689 ***	—							
4. D4	0.5 *	0.5 *	0.8 *	—						

Variable	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
Intention to use	23 **	84 **	22 **							
5. D5 Actual use	0.467 ***	0.565 ***	0.738 ***	0.795 ***	—					
6. D6 Compatibility	0.540 ***	0.626 ***	0.737 ***	0.696 ***	0.671 ***	—				
7. D7 Attitude	0.590 ***	0.602 ***	0.795 ***	0.787 ***	0.732 ***	0.798 ***	—			
8. D8 Self efficacy	0.305 ***	0.576 ***	0.666 ***	0.545 ***	0.519 ***	0.573 ***	0.591 ***	—		
9. D9 Emotional consequences of Zoom fatigue	0.138	0.152 *	0.165 *	0.144	0.094	0.210 **	0.272 ***	0.178 *	—	
10. D10 Perceived risk	-0.157 *	-0.007	-0.008	0.008	0.007	-0.038	0.027	0.024	0.418 ***	—

*** p < .05, ** p < .01, *** p < .001**

Table 2. Pearson's Correlations

Network analysis was employed to visually and statistically represent the relationships between TAM constructs and the extended variables, including perceived risk and Zoom fatigue. This approach enabled the identification of influential nodes (variables) and their connections within the network, highlighting potential mediation pathways.

The network consisted of 10 nodes (representing variables) and 27 non-zero edges out of 45 possible connections, with a sparsity index of 0.40. This indicates a moderately dense network structure where variables are interconnected.

The centrality measures and weights matrix derived from the network analysis provided critical insights into the relational dynamics among variables within the extended Technology Acceptance Model (TAM). Centrality measures, including betweenness, closeness, strength, and expected influence, highlight the relative importance of each variable in mediating and influencing connections within the network (Table 3).

Variable	Network			
	Betweenness	**Closeness**	**Strength**	**Expected influence**
1. D1 Perceived usefulness	-0.487	-0.195	-0.731	-1.115
2. D2 Perceived ease of use	-0.044	0.120	-0.244	-0.079
3. D3 Perceived enjoyment	0.399	0.722	1.413	1.309
4. D4 Intention to use	0.620	1.153	1.009	0.971
5. D5 Actual use	-0.930	-0.089	0.110	0.218
6. D6 Compatibility	-0.487	0.289	0.264	0.347
7. D7 Attitude	2.391	1.569	1.359	1.264
8. D8 Self efficacy	-0.930	-0.794	-0.819	-0.560
9. D9 Emotional consequences of Zoom fatigue	0.177	-1.209	-1.142	-0.831
10. D10 Perceived risk	-0.708	-1.566	-1.220	-1.525

Table 3. Centrality measures per variable

"Attitude" (D7) exhibited the highest centrality values across betweenness (2.391), closeness (1.569), strength (1.359), and expected influence (1.264), underscoring its pivotal role as a mediator and connector among other TAM constructs. "Perceived Enjoyment" (D3) and "Intention to Use" (D4) also demonstrated high centrality scores, reflecting their significant influence in the network. Specifically, D3 had high strength (1.413) and expected influence (1.309), suggesting its strong direct and indirect relationships with other variables. Similarly, D4 had notable closeness (1.153) and strength (1.009), indicating its accessibility and influence within the network structure. Conversely, variables such as "Perceived Risk" (D10) and "Emotional Consequences of Zoom Fatigue" (D9) exhibited negative centrality values across most metrics, indicating weaker or inverse influences on the network's relational pathways. Despite this, the weight matrix revealed significant direct connections between D10 and D9 (weight = 0.358), highlighting a notable pathway between perceived risk and the psychological impacts of Zoom fatigue.

The weights matrix further (Table 4) illustrated the direct relationships between variables. For instance, strong connections were observed between "Intention to Use" (D4) and "Actual Use" (D5) (weight = 0.452), as well as between "Perceived Enjoyment" (D3) and "Intention to Use" (D4) (weight = 0.350). These relationships validate the mediating roles of D3 and D4 within the extended TAM framework. Notably, "Attitude" (D7) was strongly connected to "Compatibility" (D6) (weight = 0.356), emphasizing its integrative function in aligning user perceptions and behaviors.

	Network									
Variable	**D1**	**D2**	**D3**	**D4**	**D5**	**D6**	**D7**	**D8**	**D9**	**D10**
1. D1 Perceived usefulness	0.000	0.154	0.084	0.033	0.000	0.064	0.161	0.000	0.000	-0.106
2. D2 Perceived ease of use	0.154	0.000	0.208	0.000	0.058	0.146	0.000	0.173	0.000	0.000
3. D3 Perceived enjoyment	0.084	0.208	0.000	0.350	0.079	0.101	0.157	0.229	0.000	0.000
4. D4 Intention to use	0.033	0.000	0.350	0.000	0.452	0.036	0.224	0.000	0.000	0.000
5. D5 Actual use	0.000	0.058	0.079	0.452	0.000	0.106	0.114	0.031	0.000	0.000
6. D6 Compatibility	0.064	0.146	0.101	0.036	0.106	0.000	0.356	0.075	0.000	0.000
7. D7 Attitude	0.161	0.000	0.157	0.224	0.114	0.356	0.000	0.061	0.119	0.000
8. D8 Self efficacy	0.000	0.173	0.229	0.000	0.031	0.075	0.061	0.000	0.009	0.000
9. D9 Emotional consequences of Zoom fatigue	0.000	0.000	0.000	0.000	0.000	0.000	0.119	0.009	0.000	0.358
10. D10 Perceived risk	-0.106	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.358	0.000

Table 4. Weights matrix

Figure 1 depicts the network structure of the extended Technology Acceptance Model (TAM), illustrating the relationships between variables as nodes and edges. The thickness of the edges represents the strength of the connections, as quantified in the weight's matrix.

Notably, key variables such as "Attitude" (D7), "Perceived Enjoyment" (D3), and "Intention to Use" (D4) are centrally positioned within the network, indicating their significant roles in mediating relationships between other constructs. Variables such as "Perceived Risk" (D10) and "Emotional Consequences of Zoom Fatigue" (D9) are positioned on the periphery, reflecting weaker or indirect connections to the core network components.

From the visual depiction in Figure 1 and the theoretical foundations of TAM, we observed critical pathways influencing "Actual Use" (D5). For example, "Compatibility" (D6) connects to "Perceived Enjoyment" (D3) and "Intention to Use" (D4), which in turn influence "Actual Use" (D5). This pathway aligns with TAM theory, where perceived usability and user attitudes are critical precursors to technology adoption behaviors (Davis, 1989).

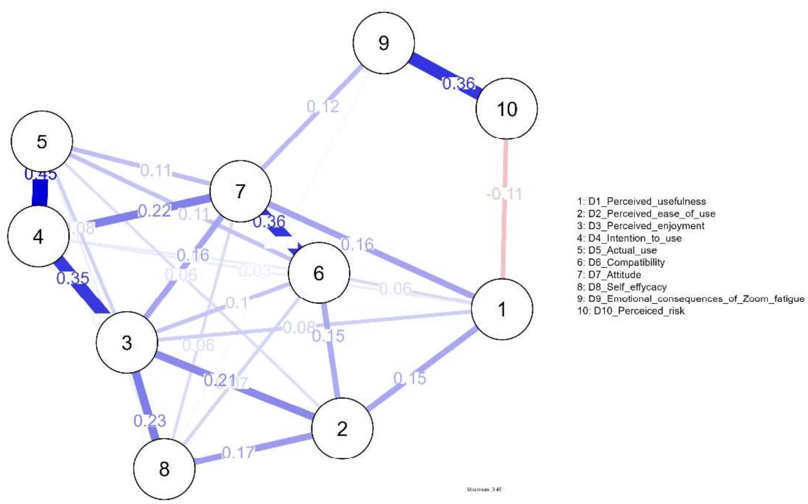

Figure 1. Network

Figure 2 provides a graphical representation of centrality measures, including betweenness, closeness, strength, and expected influence for each variable in the network. "Attitude" (D7) emerges as the most central variable, exhibiting high scores across all metrics, which underscores its integrative role in the network. "Perceived Enjoyment" (D3) and "Intention to Use" (D4) also show elevated centrality values, confirming their importance in mediating relationships and facilitating technology acceptance.

In contrast, "Perceived Risk" (D10) and "Emotional Consequences of Zoom Fatigue" (D9) exhibit lower centrality values, reflecting their peripheral roles in the network. However, these variables remain relevant, particularly in their association with psychological and emotional barriers to technology adoption. For example, "Perceived

Risk" (D10) has a strong direct connection to "Emotional Consequences of Zoom Fatigue" (D9), suggesting a pathway by which perceived risk may indirectly affect user behavior through emotional impacts.

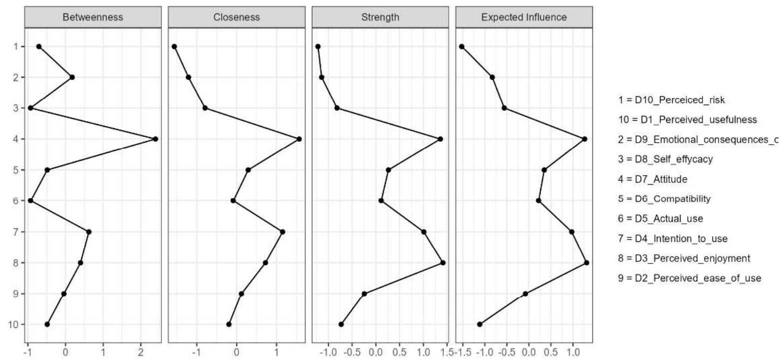

Figure 2. Centrality Plot

Next, a sequential mediation analysis statistical approach was used to understand the indirect effects of a predictor variable (X) on an outcome variable (Y) through multiple mediators arranged in a specific sequence ($M1$,$M2$,…,Mn). This analysis goes beyond simple mediation by exploring the pathways and mechanisms that link variables in complex, multistage processes. It is particularly useful in behavioral and psychological sciences, where outcomes are often influenced by both direct and indirect relationships.

One widely used tool for conducting sequential mediation analysis is the PROCESS macro developed by Andrew F. Hayes. Version 4.0 of this macro for SPSS and SAS provides a flexible and user-friendly framework for testing mediation, moderation, and conditional process models (Hayes, 2022). Among the various models available in PROCESS, Model 6 is specifically designed to assess sequential mediation, enabling researchers to examine the effects of multiple mediators in a predetermined order.

The sequential mediation analysis results provide a comprehensive understanding of the relationships between the predictor variable (Compatibility, D6D6D6), mediators (D3D3D3 - Perceived Enjoyment and D4D4D4 - Intention to Use), and the outcome variable (D5D5D5 - Actual Use).

The total effect of D6 on D5 (Effect=0.7405, p<.001) indicates that Compatibility significantly influences Actual Use. This effect encapsulates both direct and indirect influences, highlighting Compatibility's overall contribution to predicting technology adoption behaviors.

The direct effect (Effect=0.1907, p=.0095) of Compatibility on Actual Use, while significant, is smaller than the total effect, suggesting that a substantial proportion of the relationship is mediated by other variables (D3 and D4). This finding emphasizes the indirect mechanisms through which Compatibility exerts its influence.

Three specific indirect pathways were examined (Table 5):

1. **Ind1 (D6→D3→D5):** The indirect effect through Perceived Enjoyment (Effect=0.1396, p<.05) underscores the importance of enjoyment in translating Compatibility into Actual Use.
2. **Ind2 (D6→D4→D5):** The pathway via Intention to Use (Effect=0.1162, p<.05) highlights the role of intention as a crucial mediator.
3. **Ind3 (D6→D3→D4→D5):** The sequential pathway (Effect=0.2939, p<.001) accounts for the largest proportion of the total indirect effect, emphasizing the interconnectedness of enjoyment and intention in mediating the Compatibility-Actual Use relationship.

Effect Type	**Path**	**Effect**	**SE**	**t**	**p**	**LLCI**	**ULCI**	**Std. Effect**
Total Effect	D6→D5	0.7405	0.0610	12.1290	<.001	0.6200	0.8609	0.6706
Direct Effect	D6→D5	0.1907	0.0728	2.6210	.0095	0.0471	0.3343	0.1727
Indirect Effect	**Total**	0.5498	0.0651			0.4279	0.6813	0.4979
	Ind1 (D6→D3→D5)	0.1396	0.0696			0.0052	0.2852	0.1265
	Ind2 (D6→D4→D5)	0.1162	0.0463			0.0305	0.2171	0.1053
	Ind3 (D6→D3→D4→D5)	0.2939	0.0615			0.1788	0.4203	0.2662

Table 5. Sequential mediation analysis

Statistically, the significant indirect effects confirm the mediating roles of Perceived Enjoyment and Intention to Use. The confidence intervals for all pathways exclude zero, further validating the reliability of these findings. Psychologically, the results align with TAM theory, which posits that the perceptions of compatibility and enjoyment influence user intentions and behaviors. The strong sequential mediation (Ind3) underscores the interplay between emotional and cognitive factors in shaping technology adoption.

These results align with the theoretical underpinnings of the Technology Acceptance Model (TAM), which posits that user perceptions of compatibility and enjoyment are critical precursors to intention and subsequent behavior. Psychologically, this underscores the importance of designing technology systems that enhance user enjoyment and align with their existing workflows to foster positive attitudes and increase adoption rates. Statistically, the confidence intervals for all effects excluded zero, confirming the robustness of the findings. This reinforces the reliability of the sequential mediation pathways and highlights the utility of PROCESS Model 6 in capturing the nuances of multistage relationships.

In conclusion, the study demonstrates that Compatibility influences Actual Use through interconnected psychological mechanisms involving enjoyment and intention. These findings provide valuable insights for advancing TAM-based research and developing interventions that target specific mediators to enhance technology acceptance and usage.

Discussions

This study demonstrates that the integration of network analysis and sequential mediation analysis offers a robust methodological framework for exploring complex mediation relationships in behavioral research. By utilizing JASP for network visualization and SPSS Process Macro (Model 6) for sequential mediation analysis, the study successfully identified and validated key pathways within an extended Technology Acceptance Model (TAM). This dual approach was particularly valuable in addressing complex relationships where theoretical models are either highly intricate or underdeveloped.

The network analysis identified potential mediators and pathways by calculating centrality metrics and visually mapping variable relationships. Constructs such as Perceived Enjoyment (D3) and Intention to Use (D4) emerged as pivotal nodes with high centrality values, indicating their influential roles within the network. These insights guided the hypothesis that Compatibility (D6) indirectly affects Actual Use (D5) through these mediators.

Sequential mediation analysis confirmed this hypothesis. The results revealed a significant total effect (Effect=0.7405, $p<.001$) of Compatibility on Actual Use, with indirect pathways accounting for a substantial portion of this effect (Indirect Effect=0.5498, $p<.001$). The sequential pathway (D6→D3→D4→D5) was particularly prominent (Effect=0.2939, $p<.001$), demonstrating how enjoyment and intention jointly mediate the relationship between compatibility and technology adoption behaviors.

These findings align with TAM theory, which posits that user perceptions of compatibility and enjoyment are critical for fostering positive attitudes and behavioral intentions. By incorporating network analysis, this study advances TAM research by offering a systematic way to identify and test nuanced relationships among constructs, even in the absence of a fully developed theoretical framework.

Conclusions and implications

The study provides compelling evidence that sequential mediation analysis can be effectively guided by insights derived from network analysis. The integration of these methods offers several advantages for behavioral sciences:

1. **Hypothesis generation through network analysis:** By identifying key variables and pathways visually and quantitatively, network analysis serves as a powerful tool for generating hypotheses about mediation relationships.
2. **Validation through sequential mediation analysis:** Using SPSS Process Macro (Model 6), these hypotheses can be rigorously tested, allowing researchers to decompose complex relationships into direct and indirect effects.
3. **Extended TAM application:** The study demonstrated that Compatibility indirectly influences Actual Use through sequential mediators such as Perceived Enjoyment and Intention to Use. This insight expands TAM's applicability by emphasizing the role of emotional and cognitive factors in technology adoption among preschool teachers.
4. **Methodological rigor:** The use of bootstrapped confidence intervals ensured robust statistical estimates, reinforcing the reliability of the findings. The results validate the integration of exploratory (network analysis) and confirmatory (sequential mediation analysis) methodologies.

This study highlights the methodological synergy between network analysis and sequential mediation analysis. Researchers in behavioral sciences can adopt this approach to explore complex relationships, particularly when dealing with large datasets or incomplete theoretical frameworks. The visual and statistical insights from network analysis provide a strong foundation for designing sequential mediation models. For practitioners, these findings offer actionable strategies for enhancing technology acceptance. Specifically:

- **Designing user-centric systems:** enhancing compatibility and perceived enjoyment can significantly improve user attitudes and behavioral intentions, ultimately increasing Actual Use.
- **Mitigating barriers:** addressing factors such as emotional consequences (e.g., Zoom fatigue) and perceived risk can further optimize technology adoption in educational and professional contexts.

This study contributes to the ongoing evolution of TAM by incorporating constructs such as perceived risk and emotional consequences of technology use. The integration of these variables provides a more holistic understanding of the psychological mechanisms driving technology adoption.

The successful combination of network analysis and sequential mediation analysis in this study underscores their complementary strengths in uncovering and validating complex relationships. This approach bridges exploratory and confirmatory research, offering significant contributions to behavioral sciences. By demonstrating that sequential mediation relationships can be inferred and tested from network visuals, this study sets a precedent for future research in advancing theoretical and applied knowledge.

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