Coupled open innovation and dynamic capabilities: Their effect on low-tech micro and small firms' innovation

Innovación abierta acoplada y capacidades dinámicas: Su efecto en la innovación de las microempresas y pequeñas empresas de baja tecnología

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Abstract
This study examines the impact of coupled open innovation and dynamic capabilities processes on innovation performance. A Partial Least Square-Structural Equation Modelling (PLS-SEM) analysis on data from surveying a quota sample of 213 Tanzanian Micro and Small Furniture Industries (MSFIs) reveals that dynamic capabilities form sequential processes mediating the significantly positive effect of coupled open innovation on innovation performance. These findings underscore the synergy between dynamic capabilities and open innovation perspectives, emphasizing the importance for micro and small business managers and policymakers to cultivate complementary sets of dynamic capabilities for the effective realization of innovation performance

Keywords: open innovation; innovation; innovation management; innovation processes
JEL Classification: O31

Resumen
Este estudio examina el impacto de los procesos acoplados de innovación abierta y capacidades dinámicas en el rendimiento de la innovación. Un análisis de modelos de ecuaciones estructurales por mínimos cuadrados parciales (PLS-SEM) de los datos de una encuesta realizada a una muestra de 213 microempresas y pequeñas industrias del mueble tanzanas revela que las capacidades dinámicas forman procesos secuenciales que median el efecto significativamente positivo de la innovación abierta acoplada sobre el rendimiento de la innovación. Estos resultados ponen de relieve la sinergia entre las capacidades dinámicas y las perspectivas de innovación abierta, y subrayan la importancia de que los gestores de microempresas y pequeñas empresas y los responsables políticos cultiven conjuntos complementarios de capacidades dinámicas para la realización efectiva de los resultados de la innovación

Palabras clave: innovación abierta; innovación; gestión de la innovación; procesos de innovación
Clasificación JEL: O31

1. Introduction

Fast-paced technological advancements and dynamic market changes intensify the volatility, uncertainty, complexity, and ambiguity (VUCA) of today's business landscape (Schoemaker et al., 2018). In response, businesses embrace coupled open innovation, a strategy involving collaborative innovation between firms and external partners such as customers, suppliers, competitors, universities, and research institutions (Gassmann & Enkel, 2004; Hinterreger et al., 2018). These collaborations, driven by knowledge-sharing, enable firms to acquire external knowledge, facilitating the identification of innovative opportunities and the execution of complex tasks to achieve innovation performance (Cristo-Andrade & Franco, 2020; Filiou, 2020; Sesabo et al., 2023). Innovations, due to their uniqueness, capture market value, command premium prices, adapt to environmental changes, and discourage competitor replication (Teece, 2017). Consequently, coupled open innovation ultimately enhances firm performance (Martinez-Alonso et al., 2022).

Despite the significance of coupled open innovation, there are still research gaps regarding its connection to firm innovation performance. Prior research suggests that firms require sensing, seizing, and transforming capacities (dynamic capabilities) to identify external innovation opportunities, allocate resources, and adapt them for transforming opportunities into innovations, respectively (Cirjevskis, 2019; Teece, 2020). In line with Chiu et al. (2016) and Teece (2007), dynamic capabilities interconnect through sequential processes—sensing capacity, transforming capacity, and seizing capacity. Despite this, prior studies on coupled open innovation have not sufficiently delved into the sequential linkage of dynamic capabilities, which is essential for comprehending actual firm innovation processes, encompassing opportunity recognition, execution, and innovation outputs in that specific order. Existing studies that connect open innovation with sequential processes of dynamic capabilities remain anecdotal case studies requiring more quantitative cause-effect analysis of the processes (Hutton et al., 2021; Sesabo et al., 2023). Hence, there is a critical need to study the mechanism linking open innovation to firm results (Sesabo et al., 2023; Hutton et al., 2021; Teece, 2020). This research avenue is crucial for identifying dynamic capabilities that complement open innovation, especially coupled open innovation.

In response to the need to study the mechanism linking open innovation to firm results, this study analyses the effect of coupled open innovation on innovation performance through dynamic capabilities processes in micro and small furniture industries in Tanzania. The study adopts a process modelling approach based on the assumption that dynamic capabilities connect to form sequential processes (Chiu et al., 2016; Teece, 2007; Sesabo et al., 2023). Innovation processes for low-tech industries primarily follow linear innovation models (sequential process models), and the furniture manufacturing industry serves as an example of a low-tech industry (Bigliardi et al., 2020; Sesabo et al., 2023). In Tanzania, furniture manufacturing constitutes the third-largest manufacturing industry, with 97% of its firms being micro and small furniture industries (MSFIs) (United Republic of Tanzania [URT], 2016). The size of the furniture manufacturing industry in Tanzania and the high prevalence of MSFIs enhance the possibility of engaging with low-tech enterprises. Hinteregger et al. (2018) have noted the need to study low-tech industries more in the context of open innovation. Moreover, the concentration of MSFIs is optimal for fostering competitiveness (Dinh & Monga, 2013), which enhances innovation (Basit et al., 2022; Moen et al., 2018). This competitiveness and potential for innovation in MSFIs are crucial for facilitating the availability of innovation data.

This study contributes to current research in several ways. Firstly, it establishes a quantitative cause-effect link between coupled open innovation, dynamic capabilities, and innovation performance, a connection yet to be fully explored in the literature (Teece, 2020). Secondly, it sheds light on the effect of coupled open innovation on innovation performance through various processes of dynamic capabilities, providing guidance for micro and small businesses and policymakers in selecting the most effective set of dynamic capabilities for coupled open innovation. Thirdly, it tests the application of open innovation and dynamic capabilities in low-tech MSFIs in emerging African economies like Tanzania, filling a gap in quantitative research that integrates open innovation and dynamic capabilities in African economies, with the exception of Chabbouh and Boujelbene (2022).

The subsequent sections of this study follow a structured approach. Section 2 reviews the literature and formulates hypotheses for the study. Section 3 outlines the research methods used. Section 4 presents the results of the study, while Section 5 concludes the study by discussing its findings, implications, limitations, and final remarks.

2. Literature and hypothesis development

From the perspective of open innovation, coupled open innovation involves collaboration between a firm and external parties such as customers, suppliers, competitors, and institutions (Hinteregger et al., 2018). In these collaborations, external parties share ideas, information, risks, costs, and assets, enabling the firm to identify innovation opportunities and leverage technologies for executing complex innovation tasks, ultimately realizing innovation performance (Filiou, 2020; Hottenrott & Lopes-Bento, 2016; Kobarg et al., 2019). By

engaging with market and science partners, firms gain insights into market and technology opportunities, translating them into innovative products, new business models, and market expansion (Gesing et al., 2015; Yun et al., 2019). The assumption is that firms can acquire more ideas, information, and technologies for innovation by either increasing the number (breadth) of partners or by intensifying interactions with each partner (depth) (Laursen & Salter, 2006).

However, the influx of ideas, information, and technologies from multiple external partners introduces challenges related to relational management, knowledge absorption, and the risk of innovation idea leakage. These challenges may hinder innovation performance by increasing coordination costs, conflicts, confusion in idea selection, and opportunistic behaviours such as stealing innovation ideas within firms (Greco et al., 2016; Laursen & Salter, 2006; Ovuakporie et al., 2021). For instance, Martínez-Alonso et al. (2022) found that technology collaboration could reduce product innovation efficiency, depending on the type of collaboration partner in family firms. Another study by Martínez-Alonso et al. (2023) revealed that without technology protection, R&D collaboration with suppliers in family-managed firms negatively affects process innovation, but with technology protection, the effect becomes positive. Consequently, firms require the capability to protect their valuable knowledge, assign it appropriate value, and identify and leverage valuable knowledge from external partners (Chen et al., 2016; Chou et al., 2016; Seo et al., 2017).

Sensing capacity involves organizational capabilities, systems, and routines for analysing and understanding the business environment, emerging opportunities, and threats (Hodgkinson & Healey, 2011; Schilke et al., 2018; Teece, 2007). As cooperation with external parties increases, the sharing and exchange of ideas and information contribute to their analysis, thereby increasing the likelihood of firms discerning innovation opportunities (sensing capacity). Teece (2020) demonstrates that openness to dialogue with customers, suppliers, and competitors fosters an understanding of market and technological opportunities and threats (sensing capacity). Additionally, Rudolph (2017) highlights that cloud platforms enable developers to collaborate with platform users, exchanging and integrating ideas that lead to sensing innovation opportunities.

After sensing these opportunities, firms execute them through the deployment of resources. Seizing capacity is concerned with a firm's ability to mobilize resources and coordinate their use to address opportunities and capture value (Chiu et al., 2016; Teece, 2017). The sensing of innovation opportunities contributes to mobilizing resources, managing relationships, making intellectual property decisions, and developing business models to execute opportunities into innovation outcomes (Teece, 2020). Kump et al. (2019) indicate a positive effect of seizing capacity on innovation performance. Moreover, Fu et al. (2022) and Paula and Da Silver (2018) demonstrate that coupled open innovation through investment in R&D (seizing capacity) enhances innovation performance. This discussion implies that coupled open innovation enhances sensing capacity, and consequently, sensing capacity contributes to seizing capacity, enabling firms to execute innovation opportunities into innovation outputs. Formally, this discussion underlies the following hypothesis:

Hypothesis (H1): *Coupled open innovation positively affects innovation performance through sensing capacity and seizing capacity.*

A firm's seizing capacity may sometimes be constrained by existing resources, necessitating the modification of these resources to facilitate the execution of identified opportunities (Sesabo et al., 2023; Teece, 2020). For instance, managers of Micro and Small Furniture Industries (MSFIs), engaged in coupled open innovation through collaboration with external parties on social media, often identify trending furniture products (opportunities) that cannot be manufactured using outdated machines. In response, these managers opt to liquidate the old machines (transforming capacity) and adopt new temporary operation modes, such as outsourcing, while mobilizing additional funds to purchase new machines (Sesabo et al., 2023).

Similarly, marketing alliances, as examples of collaborations constituting coupled open innovation, enable banks to share their Automated Teller Machines (ATMs) to improve scale in service delivery and access new markets. In this scenario, the banks introduce new rules and regulations (transforming capacity) for sharing the ATMs and the associated value. These new operational modes, rules, and regulations represent management innovation, and the access to new markets constitutes marketing innovation (Damanpour et al., 2018; Organisation for Economic Cooperation and Development [OECD], 2018). Essentially, external knowledge sharing in coupled open innovation enables firms to sense innovation opportunities (sensing capacity). In response, these firms modify their resources (transforming capacity) to execute the opportunities. These modifications in existing resources contribute to innovation performance. Hence, coupled open innovation not only contributes to sensing capacity but also subsequently contributes to transforming capacity, ultimately leading to innovation performance. Building on this discussion, the second hypothesis is formulated as follows:

Hypothesis (H2): *Coupled open innovation positively influences innovation performance through sensing capacity and transforming capacity.*

In addition to yielding innovation outputs (performance), the modifications of resources facilitate seizing capacity. For instance, through the sale of old machines (transforming capacity), owners and managers of micro and small furniture businesses acquire additional funds for purchasing new furniture machines. Subsequently, these managers utilize such machines to execute modern furniture designs (seizing capacity) and produce innovative furniture (Sesabo et al., 2023). In essence, coupled open innovation contributes to sensing capacity. Sensing capacity, driven by the identification of innovation opportunities, leads to transforming capacity. Transforming capacity, achieved through the modification of resources, provides flexibility that enhances seizing capacity. Ultimately, seizing capacity enables the firm to mobilize and invest resources in executing innovation opportunities and achieve innovation performance. Based on this discussion, the present study formulates its third hypothesis as follows:

Hypothesis (H3): *Coupled open innovation positively influences innovation performance through sensing capacity, transforming capacity, and seizing capacity.*

In summary, as illustrated in the conceptual framework in Figure 1, coupled open innovation, facilitated by idea and information sharing, empowers firms to discern innovation opportunities (sensing capacity). Subsequently, firms mobilize and invest resources (seizing capacity) or modify existing resources (transforming capacity) to actualize these opportunities and achieve innovation performance. Furthermore, the transformation of existing resources grants firms flexibility in mobilizing resources (seizing capacity) and executing opportunities, contributing to the realization of innovation performance.

Figure 1. Conceptual framework
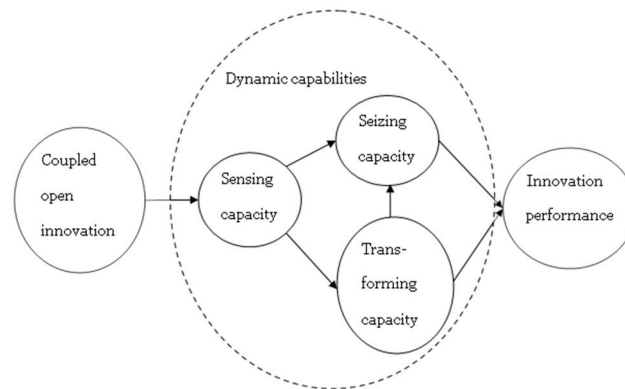
3. Data and method

3.1 Research design, sample selection, and data sources

In alignment with the study's hypotheses, a survey research design is adopted to efficiently gather a substantial quantitative dataset required for hypothesis testing (Saunders et al., 2009). The survey comprises a quota sample of 352 Micro and Small Furniture Industries (MSFIs) located in Arusha, Dar es Salaam, and Mbeya. Quotas are based on wards, which are the second lowest local government administrative areas encompassing multiple rural villages or urban streets in Tanzania (URT, 1982). Wards are chosen strategically, with furniture manufacturers in the same ward having proximity, enabling mutual learning and fostering homogeneity in furniture manufacturing innovation practices to form a quota.

Given that multiple geographically proximal wards constitute a division, the highest local administrative area following the ward in Tanzania (URT, 1982), one ward is selected from every three geographically proximal wards in each division. The chosen ward has the highest number of licensed furniture manufacturers to enhance the likelihood of sampling innovative MSFIs, as increased numbers correlate with heightened competition and innovation (Basit et al., 2022; Moen et al., 2018). The number of licensed furniture manufacturers is obtained from city trade officers, serving as a proxy for the concentration of furniture manufacturing industries in each ward. Wards are selected from different divisions to ensure a diverse representation of the cities under study.

The number of MSFIs sampled from each selected ward is contingent upon the number of licensed furniture manufacturing industries in that ward. For wards housing fewer than five, between five and ten, and over ten licensed furniture industries, the study deliberately samples three, six, and nine MSFIs, respectively. The sampling selection adheres to a criterion of achieving a one-to-one representation of highly, moderately, and less innovative MSFIs in the production of unique furniture and the use of modern production machines. Additionally, MSFIs selected from the same ward are situated on different streets to ensure diversity. This sampling approach guarantees that selected wards contribute to the MSFI sample according to the

concentration of their furniture industries. The selection of innovative MSFIs from various streets within the same ward introduces diversity and introduces variations in innovation performance. A meticulously executed quota sampling is considered as effective as stratified random sampling (Saunders et al., 2009).

Following MSFI sampling, data is collected from owner-managers using a close-ended questionnaire, translated from English to Tanzania's Swahili language to enhance clarity and facilitate self-administration, minimizing researcher bias (Saunders et al., 2009). Ultimately, 84.5 per cent (213) of the MSFIs returned usable questionnaires. The final sample comprises 62% micro furniture industries and 38% small furniture industries. In terms of ownership, the sample includes sole proprietorships (72%), partnerships (23%), companies (4%), and cooperatives (2%).

3.2 Variable descriptions and measurements

Appendix 1A outlines the items utilized in the questionnaire to measure the main variables of this study. The research involves innovation performance as a dependent variable, dynamic capabilities as mediator variables, and coupled open innovation as an independent variable.

Measuring innovation performance entailed owner-managers indicating their level of agreement on a five-point Likert scale regarding their firm's introduction of new or improved products and processes in the last three years (2017-19) compared to previous years. Based on OECD (2018), the study adopts five measurement items for new or improved products, involving the introduction of furniture products with entirely different measurements, uses, materials, components, designing techniques, and improved quality of materials and components. For new or improved processes, the study uses four measurement items concerning the introduction of production processes with entirely new or improved automation, production speed, production shape, and production quality control methods. These innovation items have been successfully employed in past studies (Jugend et al., 2018; Makanyeza & Dzvuke, 2015).

Dynamic capabilities in this study comprise three variables: sensing, seizing, and transforming capacity. The study measures these capacities using items primarily from Kump et al. (2019), with owner-managers indicating their level of agreement on a five-point Likert scale regarding their firm's implementation of these dynamic capabilities. Kump et al. (2019) double-checked the validity of their measurement items, first on firm innovation performance and subsequently on other firm performance aspects such as financial, customer, market, and employee performance indicators. Sensing capacity involves four measurement items about the firm's knowledge of best practices in the market, knowledge of competitors' activities, systematic access to new information, and access to updates on the current market situation. Seizing involves four items related to a firm's ability to turn new technological knowledge into process and product innovation, turn current information into new products or services, recognize what new information to utilize, and mobilize external resources. Transforming capacity involves four items related to the firm's success in implementing plans for changes, demonstration of strengths in implementing changes in the past, and putting change projects into practice alongside the daily business. The study adopts the fourth item of transforming capacity (Zhou et al., 2019: p. 736) concerning a firm's disposition of outdated resources.

The measurements for coupled open innovation are based on openness depth (Laursen & Salter, 2006), with owner-managers of MSFIs ranking the usefulness of cooperating for innovation with various external parties on a five-point Likert scale. The list of external cooperation parties includes customers, competitors, suppliers, universities and higher learning institutions, research and technological centres, professional or sector associations, and consultants and commercial labs (Hinteregger et al., 2018; Mazzola et al., 2016; Teplov, 2018). Openness breadth assumes that some cooperation partners are not useful while others are useful and counts only the external parties that the managers indicate to be useful; depth focuses on the intensity of cooperation with each external party (Laursen & Salter, 2006). In this study, cooperation depth is employed, operating on the assumption that the utility of cooperation for innovation can vary in reality, encompassing those that are not useful, less useful, and more useful compared to others, thereby extending beyond a binary classification of useful and not useful.

Additionally, this study controls for the effect of firm size and export intensity on innovation performance. Firm size is quantified using natural logarithms applied to the number of employees, following the approach advocated by Caputo et al. (2016) and Stefan and Bengtsson (2017). The evaluation of export intensity adopts a modification of D'Ambrosio et al.'s (2017) binary classification of yes or no sales from abroad. In this study, the assessment is refined into an ordinal scale, categorizing firms based on the proportion of sales originating from abroad, with options ranging from none to below half and more than half of sales being from abroad.

4. Research results

In investigating the influence of coupled open innovation on innovation performance through the processes of dynamic capabilities, this study employs various descriptive analysis techniques. These include Kurtosis, Skewness, Cronbach's Alpha, composite reliability, average variance extracted (AVE), hetero-trait monotrait

(HTMT) ratio, and variance inflation factor (VIF) to evaluate the suitability of the data. Subsequently, inferential analysis using PLS-SEM is applied to establish the effect of coupled open innovation on innovation performance through dynamic capabilities processes. PLS-SEM is chosen for its rigor in predicting and explaining indirect relationships, particularly in theories that are still in development (Hair et al., 2017). The integration of open innovation and dynamic capabilities is an area that still requires full theorization (Teece, 2020; West & Bogers, 2017).

4.1 Descriptive research results

The results of the descriptive analysis, as presented in Tables 1-3, confirm the suitability of the collected data for PLS-SEM analysis in this study. Table 1 reveals no significant data bias for PLS-SEM analysis, as none of the variables surpass the 5% missing value threshold, and the Kurtosis and skewness values are all below 4 (Hair et al., 2017). In Table 2, items Usenov_2 (introduction of products with different uses compared to previous ones) for innovation performance and Clab_7 (Consultants and commercial labs) for coupled open innovation were excluded as they were below the 0.4 outer loadings threshold. According to Hair et al. (2017), items with outer loadings below 0.4 should be removed as they pose a risk to variable reliability. Consequently, following the removal of items Usenov_2 and Clab_7, Table 2 confirms that the remaining items ensure the data for each variable is reliable and valid for use in PLS-SEM analysis. None of the variables fail to meet the minimum of 0.7 for Cronbach alpha and composite reliability scores, the minimum of 0.5 for AVE, and the maximum of 0.85 for HTMT ratio for validity scores (Hair et al., 2017). Additionally, Table 3 shows no common variance issues as none of the variables exceed the maximum full collinearity test score of 5 VIF (Kock, 2015).

Table 1. Descriptive statistics of variables

Construct	Mean	Median	Min	Max	Standard Deviation	Excess Kurtosis	Skewness	Number of Observations
COI	0.000	-0.017	-1.808	1.975	0.740	-0.442	0.148	213.000
IP	0.000	0.018	-2.202	1.716	0.653	0.036	-0.282	213.000
SSC	0.000	0.095	-2.316	1.913	0.869	-0.290	-0.405	213.000
SZC	0.000	0.181	-2.160	2.008	0.775	-0.037	-0.510	213.000
TRC	0.000	0.212	-2.735	1.882	0.869	-0.204	-0.498	213.000

COI (coupled open innovation); IP (innovation performance); SSC (sensing capacity); SZC (seizing capacity); TRC (transforming capacity)

Table 2. Descriptive statistics on validity and reliability of data

Construct	Cronbach α	Composite reliability	AVE	HTMT ratios IP	SSC	SZC
IP	0.883	0.914	0.641			
SSC	0.861	0.906	0.706	0.650		
SZC	0.791	0.862	0.612	0.665	0.569	
TRC	0.868	0.551	0.715	0.778	0.558	0.569
COI	0.868	0.899	0.614	0.243	0.561	0.289

Table 3. Inner VIF values for full collinearity test on common method variance

Independent variable	Dependent variable: Firm size (micro Vs. small)
COI	1.022
IP	1.522
SSC	1.048
SZC	1.062
TRC	1.511

4.2 Main research results

The results regarding the impact of coupled open innovation on innovation performance through dynamic capabilities processes, as presented in Table 4, involved comparing PLS-SEM analysis models with control variables (Model 1) and without control variables (Model 2) to determine the superior model. Both models appear to be satisfactory, as they achieved an adjusted R Square that explains a variation in innovation performance above the moderate threshold of 0.50 (Hair et al., 2017). Furthermore, based on RMS-Theta scores, both models are deemed reasonable, even though they surpass the minimum desirable fit index of 0.12 RMS-Theta. It is essential to note that this 0.12 RMS-Theta criterion was developed using Covariance-Based (CB)-SEM, where CB-SEM minimizes variance, and PLS-SEM maximizes variance between sample and population parameters. This difference allows PLS-SEM model fit indices to be relatively higher than CB-SEM model fit indices (Hair et al., 2017).

However, the findings in Table 4 suggest that the model without control variables (Model 2) outperforms the model with control variables (Model 1). The SRMS score for Model 2 is well below the maximum model fit score of 0.80 SRMS, whereas the SRMS score for Model 1 exceeds this maximum threshold. Moreover, the incorporation of firm size and export intensity as control variables in Model 1 appears to be futile, as their effects on innovation performance are insignificant. Although the effect of export intensity on innovation performance (0.067) appears statistically significant, its effect size is below Cohen's (1988) minimum effect size of 0.02.
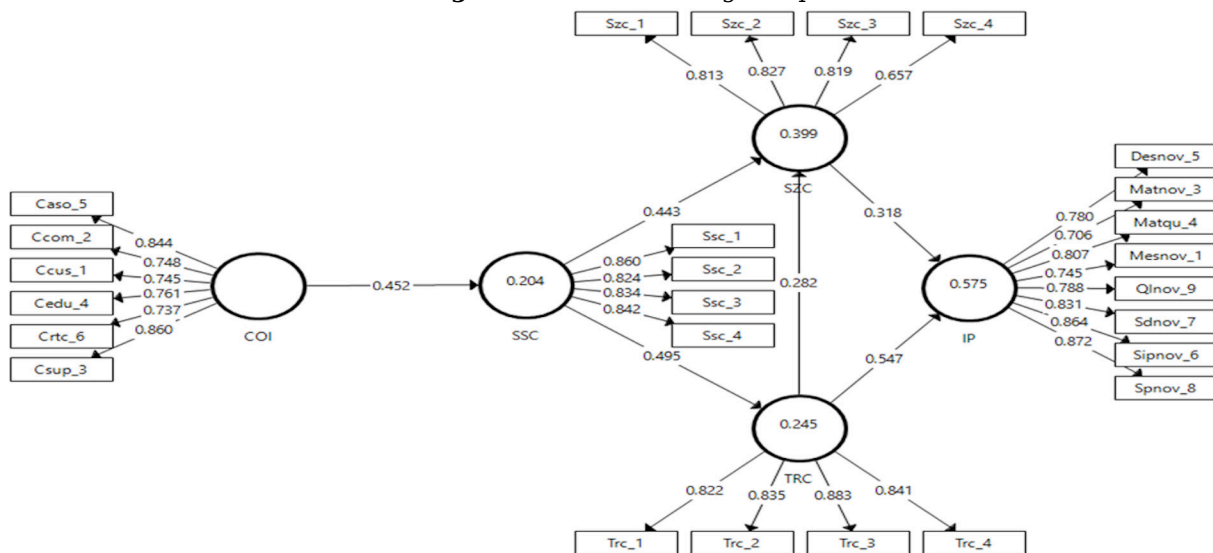
Table 4. Effect of coupled open innovation on innovation performance via dynamic capabilities

	β	Model 1 Effect size (f2)	Model 2	Model 3
Export intensity	0.067*	0.010		
Firm size	-0.001	0.000		
COI->SSC->SZC->IP	0.062		0.064	
COI->SSC->TRC->IP	0.121		0.122	
COI->SSC->TRC->SZC->IP	0.020		0.020	
COI->IP (Total indirect effect)	0.203		0.206	
COI->IP (Direct effect)				0.203*
Adjusted R square	0.571		0.571	0.037
SRMR	0.083		0.074	0.065
RMS$_{Theta}$	0.137		0.145	0.180

* p values< 0.05, bootstrap coefficient = 0; p values < 0.05, bootstrap coefficient > 0

Based on Model 2 in Table 4, the results demonstrate that coupled open innovation has a statistically significant positive effect on innovation performance through the processes of sensing capacity-seizing capacity (β = 0.062, p = 0.000 < 0.05; bootstrap coefficients = 0.035 - 0.098 ≠ 0), supporting Hypothesis 1. Additionally, the effect of coupled open innovation on innovation performance through the process of sensing capacity-transforming capacity is also significant and positive (β = 0.121, p = 0.000 < 0.05; bootstrap coefficients = 0.080 - 0.169 ≠ 0), supporting Hypothesis 2. Finally, the effect of coupled open innovation on innovation performance through the processes of sensing capacity-transforming capacity-seizing capacity is also found to be significant and positive (β = 0.020, p = 0.002 < 0.05, bootstrap coefficients = 0.010 - 0.035 ≠ 0), supporting Hypothesis 3. The total indirect effect of coupled open innovation on innovation performance through the processes of dynamic capabilities is positive (β = 0.206, p = 0.000 < 0.05, bootstrap coefficients = 0.148-0.259 > 0).

Figure 2. PLS-SEM image output

Given the results supporting the hypotheses for the indirect effects of coupled open innovation on innovation performance through the processes of dynamic capabilities, this study conducted a further analysis to test if such processes constitute mediation. Subsequently, this analysis involved excluding the processes of dynamic capabilities (supposed mediators) in Table 4 in Model 3 to determine the direct effect of coupled open innovation on innovation performance. The results reveal that when the processes of dynamic capabilities (supposed mediators) are excluded from the model, the direct effect of coupled open innovation on innovation performance becomes insignificant (β=0.203, p=0.001, < 0.05; bootstrap coefficients = -0.195 - 0.283 = 0).

An insignificant direct effect of the independent variable (coupled open innovation without the supposed mediators of dynamic capabilities) and a significant indirect effect of the independent variable through the supposed mediators (coupled open innovation through dynamic capabilities processes) indicate an indirect-only mediation (Zhao et al., 2010). Moreover, if the signs of the indirect effect and direct effect are equal (all positive), it signifies complementary mediation (Hair et al., 2017; Zhao et al., 2010). That is, the processes of dynamic capabilities are indirect-only mediators of the positive effect of coupled open innovation on innovation performance.

5. Discussion and conclusion

This study aimed to analyse the effects of coupled open innovation on innovation performance through processes of dynamic capabilities. Accordingly, the study conducted a cross-sectional survey of 213 quota-sampled MSFIs to obtain the data for the analysis and analysed them using the PLS-SEM analysis technique. Consistent with Hypothesis 1, the results of this study indicate that coupled open innovation positively affects innovation performance through the process of sensing capacity-seizing capacity. Moreover, in line with Hypothesis 2, the results indicate that coupled open innovation positively affects innovation performance through the sequential process of sensing capacity-transforming capacity. In addition, the results support Hypothesis 3 by revealing that coupled open innovation positively affects innovation performance through the process of sensing capacity-transforming capacity-seizing capacity. Further analysis of the results indicates that the processes of dynamic capabilities (sensing capacity-seizing capacity, sensing capacity-transforming capacity, and sensing capacity-transforming capacity-seizing capacity) are indirect-only complementary mediators of the positive effect of coupled open innovation on innovation performance, with the highest impact observed through the sensing capacity-transforming capacity process.

The results of this study partly support the findings of Ovuakporie et al. (2021) and Teece (2020), who argue that dynamic capabilities contribute to the effective management of open innovation, including coupled open innovation. However, this study's results differ from previous studies in terms of how coupled open innovation and dynamic capabilities collaborate to foster innovation performance.

Firstly, earlier studies (Ovuakporie et al., 2021; Teece, 2020; van Lieshout et al., 2021) linked coupled open innovation with dynamic capabilities independently of one another. Connecting dynamic capabilities independently falls short of fully explaining real firm innovation processes. For instance, linking coupled open innovation to innovation performance solely through seizing capacity (resource investment in innovation opportunities) requires additional explanations on innovation opportunity recognition (sensing capacity) and its connection to seizing capacity.

Secondly, some earlier studies (Hutton et al., 2021; Teece, 2020; van Lieshout et al., 2021) explained bi-directional relationships between dynamic capabilities and coupled open innovation without empirically testing their effects. In contrast, this study tested a specific direction of the relationship, assuming that coupled open innovation contributes to innovation performance through the processes of dynamic capabilities. As mentioned earlier, the results confirmed that dynamic capabilities form sequential processes (sensing capacity-seizing capacity, sensing capacity-transforming capacity, and sensing capacity-transforming capacity-seizing capacity) that mediate the positive effect of coupled open innovation on innovation performance. This sequential complementarity of dynamic capabilities processes suggests that these processes are systematic in such a way that the absence of one dynamic capability in a given sequence limits the enhancement of subsequent dynamic capabilities and, consequently, innovation performance. For instance, in the sequence sensing capacity-seizing capacity, if coupled open innovation fails to foster sensing capacity (opportunity recognition), there will be no opportunity to seize (seizing capacity), resulting in no innovation performance. This sequential process view of dynamic capabilities aligns with the findings of Bigliardi et al. (2020), who observed that linear (stepwise) models are still applicable in low-tech manufacturing firms.

Thirdly, Ovuakporie et al. (2021) indicated that reconfiguration (transforming capacity) moderates the positive influence of coupled open innovation on innovation performance. This moderation implies that dynamic capabilities are not entirely dependent on coupled open innovation. Similarly, Pundziene et al. (2021) suggested that dynamic capabilities enhance open innovation, indicating that dynamic capabilities are independent variables that precede open innovation. However, learning (knowledge) is considered fundamental to any resource, including dynamic capabilities (Easterby-Smith & Prieto, 2008; Teece et al., 1997). Consistent with the fundamental role of learning, this study finds that coupled open innovation, as a knowledge-sharing (learning) strategy (Greco et al., 2016), precedes (enhances) dynamic capabilities.

In general, the findings of this study confirm that coupled open innovation has a positive impact on innovation performance through sequential processes of dynamic capabilities, encompassing sensing capacity-seizing capacity, sensing capacity-transforming capacity, and sensing capacity-transforming capacity-seizing capacities. Furthermore, this study establishes that these sequential processes of dynamic capabilities serve as indirect, complementary mediators in facilitating the positive influence of coupled open innovation on innovation performance. Consequently, coupled open innovation emerges as an effective strategy for micro

and small firms to enhance their dynamic capabilities. These dynamic capabilities, in turn, complement each other in a systematic sequence, thereby contributing to improved innovation performance.

Additionally, the study reveals a nuanced positive effect of coupled open innovation on innovation performance across different sequential processes of dynamic capabilities. Notably, the most pronounced positive effect is observed in the sequential process of sensing capacity-seizing capacity. This variation in the impact of coupled open innovation through distinct dynamic capabilities processes underscores the importance for micro and small business managers, as well as policymakers, to carefully analyse and select the most effective combination of dynamic capabilities. In situations where resources for developing all dynamic capabilities are limited, prioritizing sensing capacity and transforming capacity may be strategic to establish the most efficient sensing capacity-seizing capacity process.

Theoretically, the outcomes of this study contribute to the integration of coupled open innovation and dynamic capabilities as distinct yet interconnected constructs, providing more nuanced insights into innovation performance compared to the examination of each concept in isolation. Relying solely on coupled open innovation as an external strategy falls short in comprehensively addressing internal processes involved in translating shared knowledge into tangible innovation outcomes. Similarly, dynamic capabilities alone have limitations in capturing the entirety of a firm's open innovation activities, including those related to coupled open innovation (Vanharvebeke & Cloodt, 2014).

However, it is important to acknowledge the limitations of this study. Firstly, the cross-sectional approach, while advantageous in gathering substantial and generalizable data, would benefit from a longitudinal perspective to track the evolution of variables over time and understand their implications on precedence. Future research could explore the temporal relationships among the variables in the model longitudinally. Secondly, the study's focus on a single, low-tech industry of Micro and Small Furniture Industries (MSFIs) in Tanzania, while ensuring data homogeneity, requires validation for application in other industries. Thirdly, the study omitted the examination of non-technological innovations, such as marketing and organizational innovations, on innovation performance and the application of coupled open innovation depth. Future research endeavours could explore coupled open innovation breadth (number of external cooperation partners) and its impact on non-technological innovation performance.

In conclusion, despite these limitations, the study underscores that coupled open innovation serves as an effective strategy for owner-managers of micro and small firms, particularly in the context of furniture manufacturing. It demonstrates that coupled open innovation positively influences innovation performance through sequential processes of dynamic capabilities, including sensing capacity-seizing capacity, sensing capacity-transforming capacity, and sensing capacity-transforming capacity-seizing capacity. These sequential processes of dynamic capabilities emerge as complementary mediators in the relationship between coupled open innovation and innovation performance.

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