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Measuring the DUI mode of innovation efficiently: A short-scale approach

Leonie Reher[a,b,*], Jörg Thomä[a], Kilian Bizer[a,b]

[a] *ifh Göttingen, Göttingen, Germany*
[b] *University of Göttingen, Göttingen, Germany*

Abstract

This paper advances the empirical measurement of the Doing–Using–Interacting (DUI) mode of innovation, based on the conceptual framework of Alhusen et al. (2021) and its survey-based operationalization of Reher et al. (2024b). Using data from German SMEs, we examine whether the three-dimensional structure of DUI learning theorized in the literature can be mirrored empirically. Exploratory factor analysis (EFA) confirms this latent structure by identifying three main learning processes: (1) DUI internal (learning-by-doing and internal interaction), (2) DUI user-driven (learning-by-using), and (3) DUI external (learning-by-external-interaction). However, some factor loadings are problematic, suggesting that not all of the original indicators are suitable for measuring the DUI mode of innovation. Secondly, building on the latent structure identified through EFA, short scales of various lengths are developed using Ant Colony Optimization (ACO) to address practical constraints in innovation surveys. This provides a starting point for the further development of DUI innovation indicators that are particularly suited to less RD-intensive innovation contexts, such as small firms, low-tech sectors, and lagging regions, as well as corresponding short scales.

JEL: O30, O31

Keywords: innovation measurement; innovation indicator; modes of innovation; SMEs

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*Corresponding author: reher@uni-goettingen.de

1 Introduction

In innovation measurement, both a need and an ongoing challenge is finding indicators that provide a better understanding of business innovation activities that extend beyond the narrow scope of in-house research and development (R&D) (Gault, 2013, 2018). In this context, Jensen et al. (2007)'s framework of innovation modes is a key conceptual contribution to a more nuanced understanding of the various ways in which firms can innovate (for literature reviews, see Apanasovich (2016); Santos et al. (2022)). This framework differentiates between two principal modes of innovation: the Science-Technology-Innovation (STI) mode, which relies heavily on formal R&D and explicit, codified scientific knowledge, and the Doing-Using-Interacting (DUI) mode, which emphasizes informal, experience-based learning processes. This mode recognizes that firms can innovate through practical knowledge, organizational routines, and interactions with customers, suppliers, and other non-science-based stakeholders, in addition to, or even without, formal R&D. The innovation mode concept has been applied in a number of studies. For instance, it has been used to analyze innovation activities in SMEs (e.g. Hervás-Oliver et al., 2021; Parrilli et al., 2023; Parrilli and Radicic, 2021; Thomä and Zimmermann, 2020); to evaluate the supporting role of DUI in terms of a firm's absorptive capacity (e.g. Haus-Reve et al., 2023; Weidner et al., 2023); to explain regional variations in innovation, particularly with regard to innovation in peripheral or lagging regions (e.g. Doloreux and Shearmur, 2023; Doloreux et al., 2024; Hädrich et al., 2024; Hervás-Oliver et al., 2021; Reher et al., 2024a); or to enhance our understanding of the complementary and mutually reinforcing interactions between DUI and STI types of learning (e.g. Alhusen and Bennat, 2021; Parrilli and Heras, 2016; Thomä, 2017).

However, while STI innovation activities are realtively easy to measure, there remains a notable lack of consistent, theoretically grounded instruments for measuring the DUI mode of learning and innovation at the firm level (see Reher et al. (2024b), for an overview of the relevant literature). Existing studies often rely on different — and frequently improvised — indicators and methods, either by focusing only on selected components of the DUI mode or by constructing broader composite indices that lack measurement accuracy. Overall, DUI measurement is therefore still ad hoc and lacks coherence across studies. Therefore, in order to advance empirical investigations of the DUI innovation mode — for example, with regard to it's role in different types of firms and regional innovation contexts — it is crucial to develop suitable and coherent indicators and corresponding survey items.

In a seminal effort to lay the groundwork for a more accurate DUI measurement in future research, Alhusen et al. (2021) propose a conceptual framework that organizes DUI-related innovation activities into three overarching dimensions. The authors further refined this structure into more specific categories based on qualitative interviews, deriving an extensive set of indicators intended to capture the multifaceted nature of DUI learning processes. Reher et al. (2024b) built on this conceptual foundation by applying this set of 47 indicators empirically for the first time in a quantitative survey. Their empirical findings demonstrate that various forms of DUI-based learning activities are significant predictors of innovation outcomes in German SMEs in general and, as expected, particularly in the less R&D-intensive knowledge environments of lagging regions. This shows the empirical relevance of the DUI measurement framework conceptualized by Alhusen et al. (2021).

Nevertheless, Reher et al. (2024b)'s study also reveals significant practical challenges in implementing Alhusen et al. (2021)'s extensive indicator set in broader empirical studies. Large-scale surveys are typically limited by the length of the questionnaire and the resulting burden on respondents; as a result, there is usually a negative correlation between the length of the questionnaire and response rates (Rammstedt and Beierlein, 2014). Consequently, it would be impractical to incorporate all the proposed DUI indicators in large-scale innovation surveys. Hence, building on Alhusen et al. (2021)'s conceptual work in developing a DUI measurement framework, and Reher et al. (2024b)'s subsequent empirical demonstration of its practical relevance, the next step is clear: to develop a valid short scale that captures the essential dimensions of the DUI mode while saving space and ensuring practicality for future quantitative studies.

Against this background, this paper makes two contributions using data from a quantitative survey conducted by Reher et al. (2024b) on the basis of the Alhusen et al. (2021) measurement framework. Firstly, we empirically examine the latent dimensionality underlying the proposed DUI measurement framework. This involves analyzing the factor structure of the surveyed data using an exploratory factor analysis (EFA) and assessing the suitability of individual indicators for capturing the emergent factors. This analysis step enables us to assess the alignment of our indicator data with the theoretically developed DUI mode dimensions of

Alhusen et al. (2021). Secondly, based on these findings, we develop a series of short scales of varying lengths using Ant Colony Optimization (ACO). These scales are designed to efficiently capture the core elements of the DUI mode within the constraints of typical survey lengths. Our results suggest that not all of the original indicators proposed by Alhusen et al. (2021) are suitable for representing the latent structure of the DUI mode. Nevertheless, the empirically derived factor structure closely corresponds to the three broader dimensions conceptualized in Alhusen et al.'s (2021) measurement framework, thereby lending support to its theoretical foundations. The derived short scales demonstrate satisfactory model fit and factor saturation. This provides a promising starting point for the further refinement and validation of DUI short scales in future research.

The paper proceeds as follows: Section 2 elaborates on the concept and dimensions of DUI learning, and on the method used to develop corresponding short scales for large-scale surveys. Section 3 describes the data and methodology employed. The results are presented in Section 4. Finally, Section 5 discusses and summarizes our findings, formulating implications for innovation measurement and further research.

2 Background

2.1 Concept and empirical measures of DUI learning

While its very label — 'Doing, Using, and Interacting' (DUI)— already implies a multidimensional structure of heterogeneous learning processes that collectively constitute this mode of business innovation, existing measurement approaches have thus far been largely selective and fragmented, lacking conceptual coherence (Reher et al., 2024b). For example, many existing empirical studies rely on an ad hoc selection of indicators drawn from existing data sources, such as the Community Innovation Survey, to operationalization the DUI mode. This has led to a disproportionate emphasis on DUI interaction with external actors — such as customers or suppliers while neglecting other facets of DUI learning, particularly those rooted in internal processes such as experiential learning, employee involvement, or organizational routines (Haus-Reve et al., 2023). Recent empirical contributions have increasingly challenged this narrow conceptualization, calling for a more comprehensive and differentiated understanding of the DUI mode. More specifically, they differentiate between internal and external innovation activities, creating dimensionality in terms of whether DUI learning takes place inside or outside the company (e.g., Doloreux and Shearmur, 2023; Haus-Reve et al., 2023; Parrilli and Radicic, 2021; Piercey et al., 2025). This distinction reflects a more nuanced understanding of where and how DUI learning occurs at the firm level, whether through intra-organizational processes and internal knowledge accumulation or interactive learning in the firm's external environment.

From a conceptual perspective, the inconsistency and lack of comprehensiveness in the empirical measurement of the DUI mode is addressed for the first time by Alhusen et al. (2021). Based on previously used DUI indicators in the literature, as well as data from interviews with SME representatives and regional innovation consultants, Alhusen et al. (2021) develop a set of 47 indicators, grouping them into 15 categories and assigning them to three broader DUI dimensions:

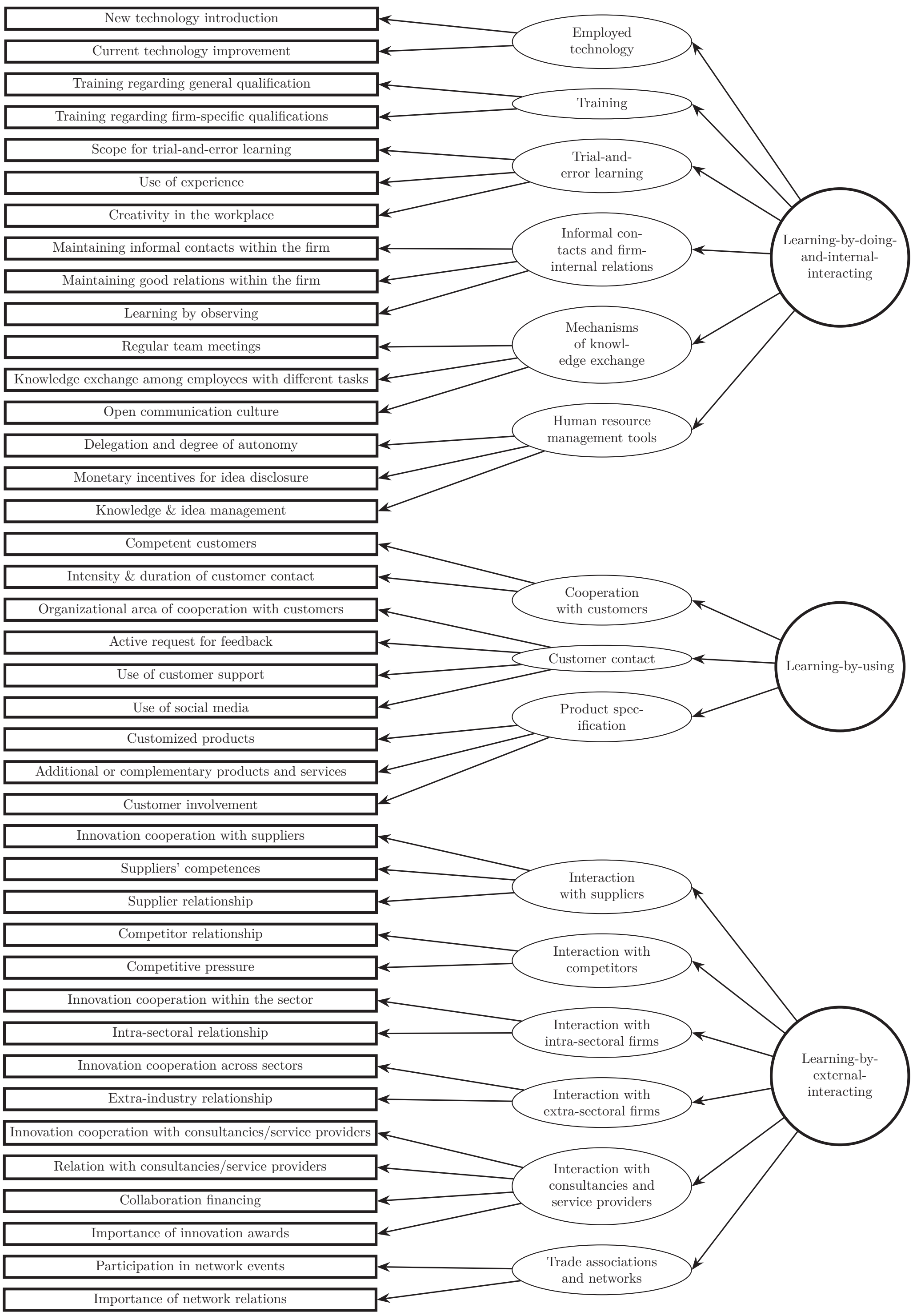
- **Learning-by-doing and learning-by-internal-interacting** describes the within-firm importance of employed technology, training, trial-and-error learning, (informal) knowledge exchange, or human resource management during the innovation process.
- **Learning-by-using** refers to the utilization of customer knowledge in innovation through cooperation, customer contact or product specification.
- **Learning-by-external-interaction** encompasses innovation-related learning through interaction with suppliers, competitors, intra- and extra-sectoral firms, consultancies, and public institutions, as well as recognizing the importance of networks and trade associations.

The indicator set conceptualized and developed by Alhusen et al. (2021) was applied in an empirical study for the first time by Reher et al. (2024b), as part of a dedicated quantitative survey conducted among SMEs in Germany. For this purpose, the authors translated the indicator set into a battery of 40 survey questions. A detailed mapping of these questions to the original measurement framework can be found in Table A.1. Based on their data, Reher et al. (2024b) find that the Alhusen et al. (2021) indicators are actually suitable for predicting innovation drivers in SMEs, highlighting that DUI learning goes beyond external interactions. Their results show that the impact of DUI learning varies by region and innovation type. In particular, according to their results, innovation in lagging regions is closely linked to the DUI mode, especially through intra-firm learning processes.

From a methodological perspective, Reher et al. (2024b) categorises the individual DUI indicators into three overarching DUI dimensions, as originally defined by Alhusen et al. (2021). While this classification is conceptually plausible and grounded in the original framework, it is somewhat rigid in that it does not account for correlations and interactions across dimensions. To address this to some extent, Reher et al. (2024b) supplement their dimensional analysis with item-level evaluations, providing more detailed insights into individual DUI-related innovation practices. However, they do not empirically test the latent factor structure of the DUI framework or validate the theoretical dimensionality through statistical modeling. Furthermore, their analysis highlights the necessity of constructing short scales of the Alhusen et al. (2021) measurement framework as alternative measures for use in large-scale surveys. In their study, Reher et al. (2024b) address the challenge of conducting a quantitative survey that includes the broad set of DUI indicators proposed by Alhusen et al. (2021). This led to a lengthy questionnaire and required the use of machine learning approaches to analyze the large amount of data collected. They therefore concluded that short, manageable scales are needed with regard to the Alhusen et al. (2021) measurement framework to acknowledge the practical constraints related to the limited space available in large-scale innovation surveys. Although shorter and more compact, these scales should reflect the full scope of the DUI mode so that future studies would no longer have to rely on incomplete or selective indicators for DUI learning.

The present study is based on a synthesis of the measurement framework conceptualized by Alhusen et al. (2021) and its subsequent operationalization by Reher et al. (2024b) into practical innovation measurement items, as illustrated in Figure 1 (see Table A.1 for the specific survey questions). Specifically, we adopt the three high-level dimensions of DUI mode innovation initially proposed by Alhusen et al. (2021). Additionally, we acknowledge the 15 intermediate categories nested within these dimensions, as outlined in the original framework. Our analysis also relies on the 40 survey indicators formulated and implemented by Reher et al. (2024b), which provide full empirical coverage of the original set of indicators. This integrated framework forms the basis of our empirical assessment of the latent factor structure of the DUI mode and the subsequent development of short scales to measure DUI learning along its different dimensions and facets.

Figure 1: An integrated measurement framework – DUI dimensions and their empirical measures



Source: Own compilation based on Alhusen et al. (2021) and Reher et al. (2024b).

2.2 Short scale construction

A fundamental methodological trade-off arises in the empirical measurement of DUI mode learning: on the one hand, it is necessary to capture its inherently multifaceted and multidimensional nature as comprehensively as possible; on the other hand, practical constraints, such as limited space in standardized innovation surveys or the need to minimize the number of parameters in multivariate regression models, demand parsimony in terms of the number of questions included in a questionnaire (Rammstedt and Beierlein, 2014; Ziegler et al., 2014). This tension provides a clear rationale for developing an abbreviated version of the indicator set proposed and tested by Alhusen et al. (2021) and Reher et al. (2024b) which still adequately represents the underlying dimensions of DUI mode learning.

The construction of short scales is a well-established practice in fields such as psychology, educational measurement, and the health sciences (Schroeders et al., 2016). Prominent examples include the development of numerous shortened versions of the Big Five personality inventory (see e.g. Olaru et al., 2015; Yarkoni, 2010). The primary objective of such efforts is to reduce the number of survey items significantly while maintaining acceptable levels of psychometric quality, particularly in terms of reliability and validity (Steger et al., 2023). To achieve this goal, researchers have increasingly turned to machine learning-based optimization techniques tailored specifically to solve combinatorial problems. The most prominent of these are Ant Colony Optimization (ACO) (e.g. Jankowsky et al., 2020; Olaru and Jankowsky, 2022; Partsch et al., 2024; Schroeders et al., 2024) and Genetic Algorithms (GA) (e.g. Eisenbarth et al., 2015; Sahdra et al., 2016), which offer powerful alternatives to more traditional item selection methods such as Classical Test Theory (CTT), Factor Analysis, or Item Response Theory (IRT) (for an overview, see Kruyen et al., 2013). Empirical comparisons have demonstrated ACO's superior performance in developing short scales that optimize multiple criteria simultaneously while preserving the integrity of the original instrument (Olaru et al., 2015; Schroeders et al., 2016).

Against this backdrop, the present study applies state-of-the-art machine learning techniques to identify a subset of indicators on the basis of the integrated measurement framework presented in Figure 1 (see Subsection 2.1) that can be used to construct parsimonious and robust short scales for measuring the DUI mode of innovation. This approach aims to reconcile the need for conceptual comprehensiveness with the practical requirements of empirical research settings. At the same time, it should be emphasized that this is only a first step. The present study is the first of its kind to address the issue of developing short scales in the context of DUI mode measurement. In this respect, our study lays the groundwork for future research in this area, which will refine and validate the short scales developed here.

3 Data and Method

3.1 Data

The empirical analysis is based on primary data collected through a quantitative online survey targeting SMEs in Germany. Conducted in July 2023, the survey was based on a nationwide random sample and specifically designed to capture detailed information on innovation activities, with a specific focus on the DUI mode. Company contact information was sourced from the Creditreform database, maintained by Germany's largest credit reference agency and providing company data on economically active businesses from all sectors of the economy. In line with the standard SME definition used by the European Commission, the sample was restricted to private-sector enterprises with no more than 249 employees. Chief executive officers (CEOs) were invited to participate in an online survey via a personalized access link in a postal invitation. The survey included all the items operationalized by Reher et al. (2024b), based on the Alhusen et al. (2021) measurement framework (see Figure 1 and Table A.1). The aim was to provide a comprehensive and detailed assessment of a firm's DUI learning activities. Following standard data cleaning procedures, including the removal of incomplete responses and inconsistent entries, a final sample of 429 questionnaires was retained for the empirical analysis. This dataset includes full responses to all of the 40 DUI-related survey items (i.e. 40 DUI indicators) from Reher et al. (2024b), a prerequisite for the multivariate and factor-analytic techniques employed in this study. Descriptive statistics for the variables included in the analysis are presented in Table A.1.

3.2 Method

We first employ Exploratory Factor Analysis (EFA) to identify the underlying latent constructs of DUI learning and develop an initial model for subsequent optimization. This approach is appropriate given that the empirical structure of the DUI mode, particularly in relation to the comprehensive measurement framework proposed by Alhusen et al. (2021), has not yet been empirically validated using data-driven factor analytic methods.[1] When conducting the EFA, we applied oblique (oblimin) rotation, which allows for correlation among the latent factors — an assumption that is consistent with the theoretical expectation of the interconnectedness of DUI dimensions. To ensure conceptual clarity and statistical robustness, we only retained indicators that loaded at least 0.40 on a single factor and exhibited no substantial cross-loadings (i.e. high loadings on multiple factors). This filtering step serves two purposes. Firstly, it ensures that each retained indicator meaningfully contributes to the definition of a single latent construct. Secondly, it is the first stage in reducing the number of survey items, paving the way for the subsequent development of short scales that preserve the multidimensional nature of the DUI mode while reducing respondent burden.

Subsequent to the EFA, we use Ant Colony Optimization (ACO) to construct short scales of different lengths based on the empirically identified factor structure. There are two primary reasons why we have chosen to develop short scales of varying lengths of 10 to 20 survey items. Firstly, as this is the first study in this context and we wish to lay the groundwork for the future refinement, adaptation and validation of the short scales developed, we aim to provide a 'corridor' of between 25 and 50 percent of items suitable for a short scale in relation to the initial set of 40 survey questions on DUI indicators provided by Reher et al. (2024b). This will enable future studies to test or validate two or more short scales of different lengths simultaneously. Secondly, having greater flexibility in the length of the scale means that the provided measurement instrument — i.e. short scales of various lengths for measuring the DUI mode — can be adapted to individual constraints. This is particularly useful for large-scale innovation surveys where space is limited. Depending on the specific application, the preferred length of the required DUI short scale may vary.

Hence, unlike previous studies which typically construct a single short scale or predefine a fixed number of scale versions based on uniform item allocation strategies such as proportional distribution across dimensions or equal numbers of items per factor (see e.g. Olaru and Jankowsky, 2022; Schroeders et al., 2016), our approach introduces two additional levels of flexibility into the optimization process. Specifically, we implement an iterative loop within the ACO algorithm that: (i) systematically evaluates all possible combinations of item allocations per factor, subject to the constraint that a minimum of three items must be selected for each latent DUI dimension to ensure content validity and factorial identification; and (ii) varies the total scale length across the predefined range of 10 to 20 survey items, allowing the algorithm to identify optimal short scales of varying lengths. The number of possible combinations for selecting k out of the survey items with a minimum of three items per factor i thus responds to

$$\sum_{\substack{x_1+x_2+\cdots+x_F=k \\ x_i\geq 3 \ \forall i}} \prod_{i=1}^{F} \binom{n_i}{x_i}$$

where

- F is the number of factors, indexed by $i = 1, 2, \ldots, F$.
- n_i is the number of items available in factor i.

[1]Olaru et al. (2019) emphasize the importance of establishing conceptual alignment between the measurement model and theoretical expectations before selecting items for short scale development. When a clearly specified theoretical structure is available, Confirmatory Factor Analysis (CFA) can be used instead of EFA to derive an initial model. For this reason, we also tested the theoretical structure of the DUI data obtained through our survey using first- and second-order CFAs. In the first-order model, indicators were assigned to the three broader DUI dimensions and the latent constructs were allowed to correlate. However, the fit statistics reported in Table A.2 indicate that the theoretical model does not adequately reflect the empirical data – a finding consistent with our EFA results in Section 4, which suggests that some of the 40 indicators are not suitable for measuring the intended dimensions. The second-order CFA, which attempts to model intermediate categories between the three overarching dimensions and their specific indicators, was affected by convergence issues, likely due to the small number of indicators per intermediate category. In light of these limitations, we conclude that EFA is the more appropriate approach in this context, particularly given that our aim is to develop a new measurement instrument based on previously untested data with an unknown underlying factor structure.

- k be the total number of items to be selected.
- x_i is the number of selected items from factor i.

These two levels of flexibility enable a more nuanced and context-sensitive balance between brevity and measurement precision, while preserving the multidimensional structure of the DUI innovation mode, as revealed by the EFA. The outcome is a set of empirically optimized short scales that vary in length and composition, yet are all rooted in a shared latent factor structure. This provides a flexible toolkit for future empirical studies.

ACO is a highly effective algorithmic approach to constructing short scales, as demonstrated in the context of modern psychometrics and machine learning applications (Leite et al., 2008; Olaru et al., 2015; Schroeders et al., 2016). It belongs to the class of bio-inspired metaheuristic optimization techniques and is modeled on the foraging behavior of ants, specifically the process by which they discover the shortest path to a food source. This process relies on the cumulative deposition of pheromone traces along traveled paths. While ants initially explore multiple routes at random, the shortest route gradually accumulates the highest concentration of pheromones. This increases the likelihood that subsequent ants will follow and reinforce this path (for a detailed explanation, see Dorigo et al., 1996). Translating this biological principle into algorithmic logic, ACO is used to construct short scales and optimize the representation of a latent construct using a limited number of items. In this context, item combinations are randomly generated and evaluated against predefined optimization criteria. Each solution (i.e. a parsimonious set of selected items) is scored based on how well it meets these criteria, and those with superior performance exert greater influence over future iterations of the algorithm. Through repeated sampling and probabilistic reinforcement, the algorithm converges on an optimal or near-optimal configuration of items. Following the implementation provided in the `R` script by Olaru et al. (2019), we apply ACO to select item subsets that provide an optimal balance between conceptual rigor and scale brevity. As optimization criteria, we adopt a combination of widely accepted thresholds for model fit and reliability (e.g. Hu and Bentler, 1999; Leite et al., 2008; Olaru and Jankowsky, 2022). Specifically, we require a Comparative Fit Index (CFI) of at least 0.95, a Root Mean Square Error of Approximation (RMSEA) of no more than 0.06, and a Standardized Root Mean Square Residual (SRMR) of no more than 0.06 resulting in the following model fit criterion:

$$\varphi_{Fit} = \frac{1}{3}\left(\frac{1}{1+e^{95-100CFI}} + \frac{1}{1+e^{6-100RMSEA}} + \frac{1}{1+e^{6-100SRMR}}\right) \tag{1}$$

For reliability, we employ McDonald's Omega (ω) with a threshold of $\omega \geq .70$:

$$\varphi_{Rel} = \frac{1}{1+e^{7-10\omega}} \tag{2}$$

The final optimization criterion is the sum of these criteria:

$$\varphi_{overall} = \varphi_{Fit} + \varphi_{Rel} \tag{3}$$

Due to the ordinal nature of our survey items, we use the weighted least square mean and variance adjusted estimator (WLSMV) (see Leite et al., 2008; Olaru et al., 2019). For each of the derived short scales, we run the algorithm five times with five random seeds, as ACO is a heuristic algorithm that does not guarantee optimality (Leite et al., 2008). In the results section, we present the best solution from these five runs (see Neumann et al., 2023; Schroeders et al., 2016; Volz et al., 2021). Table 1 summarizes the various input criteria for the ACO in the present study.

Table 1: Input for ACO

Number of models (ants) estimated per iteration	50
Evaporation multiplier (determines selection probability)	0.95
Model type	CFA
Estimator	WLSMV
Comparative Fit Index (CFI)	>0.95
Root mean square error of approximation (RMSEA)	<0.06
Standardized root mean square residual (SRMR)	<0.06
McDonald's ω	>0.7
Maximum number of iterations without improvement in optimization	30
Number of random seeds	5

4 Results

4.1 EFA

The EFA revealed a latent structure underlying the surveyed DUI indicators consisting of 28 items loading onto three distinct factors (see Table 2). Notably, this empirically derived structure reflects the tripartite division of dimensions originally proposed by Alhusen et al. (2021): 'learning-by-doing-and-internal-interacting', 'learning-by-using', and 'learning-by-external-interacting'. Hence, despite the necessary reduction in the number of indicators, this structure lends empirical support to the conceptual framework.[2] Of the original 40 DUI indicators, twelve had to be excluded from the final factor model because they either had insufficient factor loadings (i.e. below 0.40 on any factor) or problematic cross-loadings, i.e. a single item exhibited high loadings on multiple factors, thus failing to demonstrate clear factorial alignment.

The first factor is characterized by high loadings of indicators that capture intra-firm learning processes; thus, we label this factor 'DUI internal'. The items with the highest loadings on this factor are *Maintaining good relations within the firm* (0.765), *Maintaining informal contacts within the firm* (0.756) and *Scope for trial-and-error learning* (0.731). The second factor comprises items relating to the interaction with customers and users, consistent with the 'learning-by-using' component of the Alhusen et al. (2021) measurement framework, and is labeled 'DUI user-driven'. Prominent indicators include *Use of customer support* (0.718) and *Organizational area of cooperation with customers* (0.640). The third factor captures learning through interaction with other external actors. It is therefore labeled 'DUI external'. Items such a *Innovation cooperation with consultancies/service providers* (0.770) or *Collaboration financing* (0.691) exhibit the highest loadings for this factor. Taken together, the EFA results confirm the multidimensionality of the DUI mode and provide an empirical basis for the subsequent development of short scales that preserve the conceptual distinctions between internal, user-driven, and external learning processes.

[2] To determine the appropriate number of factors to retain, we applied the elbow criterion (scree test), as illustrated in Figure A.1 in the Appendix. Although the Kaiser criterion (Eigenvalue > 1) indicated that a five-factor solution was also possible, we opted for a three-factor solution, as this was identified as being the most meaningful in explaining the underlying latent structure of our data.

Table 2: EFA

Dimension in Alhusen et al. (2021)	Item	DUI internal	DUI user-driven	DUI external	Uniqueness
Learning-by-doing and learning-by-internal-interacting	Maintaining good relations within the firm	**0.765**	-0.009	0.053	0.390
	Maintaining informal contacts within the firm	**0.756**	-0.030	-0.013	0.458
	Scope for trial-and-error learning	**0.731**	-0.025	-0.030	0.499
	Open communication culture	**0.681**	0.088	-0.086	0.506
	Delegation and degree of autonomy	**0.656**	0.024	0.005	0.550
	Knowledge exchange among employees with different tasks	**0.652**	0.054	0.060	0.501
	Learning by observing	**0.634**	0.013	-0.049	0.610
	Regular team meetings	**0.631**	0.098	-0.020	0.538
	Creativity in the workplace	**0.626**	0.022	-0.004	0.595
	Knowledge & idea management	**0.563**	0.108	0.081	0.562
	Monetary incentives for idea disclosure	**0.484**	0.081	0.097	0.669
	Training regarding general qualification	**0.451**	0.081	0.151	0.671
	New technology introduction				
	Current technology improvement				
	Training regarding firm-specific qualifications				
	Use of experience				
Learning-by-using	Use of customer support	0.089	**0.718**	-0.088	0.449
	Organizational area of cooperation with customers	0.187	**0.640**	-0.003	0.430
	Additional or complementary products and services	0.026	**0.596**	0.111	0.569
	Customer involvement	0.044	**0.570**	0.232	0.498
	Active request for feedback	0.219	**0.547**	-0.015	0.535
	Customized products	0.053	**0.541**	0.137	0.601
	Intensity & duration of customer contact	0.092	**0.496**	-0.058	0.716
	Competent customers				
	Use of social media				
Learning-by-external-interacting	Innovation cooperation with consultancies/service providers	-0.002	0.048	**0.770**	0.381
	Relation with consultancies/service providers	-0.042	0.117	**0.723**	0.434
	Collaboration financing	-0.074	-0.029	**0.691**	0.564
	Importance of innovation awards	0.017	-0.026	**0.660**	0.568
	Importance of network relations	0.206	-0.172	**0.624**	0.554
	Participation in network events	0.227	-0.261	**0.618**	0.565
	Innovation cooperation across sectors	-0.054	0.348	**0.565**	0.470
	Innovation cooperation within the sector	0.002	0.226	**0.535**	0.583
	Extra-industry relationship	0.051	0.332	**0.429**	0.576
	Innovation cooperation with suppliers				
	Suppliers' competences				
	Supplier relationship				
	Competitor relationship				
	Competitive pressure				
	Intra-sectoral relationship				

Notes: Results from exploratory factor analysis with oblimin rotation. Blanks indicate variables with loadings of < 0.4; the corresponding survey items have therefore been deleted.

4.2 Flexible ACO

Building on the factor structure identified through the EFA, we apply ACO to derive a set of optimized short scales within the predefined range of 10–20 survey items (see Subsection 3.2), representing the identified multidimensional nature of DUI learning. Table 3 shows the results of this optimization procedure, including the specific items selected for inclusion in each short scale, as well as the number(s) of the random seed(s) that yielded the best overall optimization score ($\varphi_{overall}$) across five independent algorithm runs. It also shows the associated model fit and reliability statistics, as well as the number of possible combinations considered in the respective short scale construction.[3]

Several patterns emerge across the ACO runs. Three items are consistently selected in all short-scale variants, regardless of length: *Training regarding general qualification*, *Delegation and degree of autonomy*, and *Innovation cooperation within the sector.* These items appear to represent core elements of the DUI mode,

[3]Although $\varphi_{overall}$ is as an effective selection criterion for identifying the best-performing model within a given scale length, it is not suitable for determining the optimal scale length across models of different sizes. This is because $\varphi_{overall}$ tends to decrease as the number of items increases, thereby making comparisons across scale lengths difficult.

providing robust and reliable coverage of the underlying factors. Conversely, three items are excluded from all resulting scales: *Scope for trial-and-error learning*, *Monetary incentives for idea disclosure*, *Collaboration financing*. Their exclusion may be due to either conceptual overlap with stronger items or poor statistical performance during the optimization process. Notably, the DUI-10 and DUI-12 scales demonstrate lower robustness. This is evident from the fact that their respective item sets are selected in only one out of five algorithm runs, and the composition of the selected items differs significantly from that of the longer scales. This is most evident for the "DUI user-driven" dimension, where only the bottom three items are selected for these two scales which is not observed in any of the other short scales. These two scales may be more susceptible to random fluctuations in the optimization process, which aligns with existing findings in the literature indicating that many statistically equivalent models can emerge from high-dimensional search spaces with multiple viable solutions (Olaru et al., 2019). Starting with the DUI-13 scale, a pattern of nestedness emerges: shorter scales tend to form subsets of longer scales. All resulting models across the different lengths demonstrate good model fit — based on established thresholds for CFI, RMSEA, and SRMR — and high levels of reliability. This confirms the overall suitability of ACO as a tool for generating concise, yet conceptually and statistically sound short scales for capturing the different dimensions of DUI-based learning and the corresponding innovation activities.

Table 3: Results of ACO

	Survey item	DUI-10	DUI-11	DUI-12	DUI-13	DUI-14	DUI-15	DUI-16	DUI-17	DUI-18	DUI-19	DUI-20
DUI internal	Training regarding general qualification	x	x	x	x	x	x	x	x	x	x	x
	Scope for trial-and-error learning											
	Creativity in the workplace						x	x	x	x	x	x
	Maintaining informal contacts within the firm										x	x
	Maintaining good relations within the firm	x	x	x	x	x	x	x	x	x		
	Learning by observing										x	x
	Regular team meetings	x		x				x	x	x	x	x
	Knowledge exchange among employees with different tasks		x		x	x	x		x	x		x
	Open communication culture								x	x	x	x
	Delegation and degree of autonomy	x	x	x	x	x	x	x	x	x	x	x
	Monetary incentives for idea disclosure											
	Knowledge & idea management		x	x	x	x	x	x	x	x	x	x
DUI user-driven	Intensity & duration of customer contact				x	x	x	x	x	x	x	x
	Active request for feedback		x		x	x	x	x	x	x	x	x
	Use of customer support				x	x	x	x	x	x	x	x
	Organizational area of cooperation with customers		x		x	x	x	x	x	x	x	x
	Customized products	x		x						x	x	x
	Additional or complementary products and services	x	x	x		x	x	x	x	x	x	x
	Customer involvement	x		x								
DUI external	Innovation cooperation within the sector	x	x	x	x	x	x	x	x	x	x	x
	Innovation cooperation across sectors	x	x		x	x	x	x		x	x	x
	Extra-industry relationship			x	x	x	x	x	x	x	x	x
	Innovation cooperation with consultancies/service providers	x	x									
	Relation with consultancies/service providers			x	x	x	x	x	x	x	x	x
	Collaboration financing											
	Importance of innovation awards										x	x
	Participation in network events			x				x	x			
	Importance of network relations			x				x	x			
Random seed run (numbers from 1 to 5)		2	2,3,4,5	1	1,5	1,2,4,5	1,2,4,5	1,2,3,4,5	1,3,4,5	1,3,4	3,4,5	1,2,3,4,5
Optimization criteria												
$\varphi_{overall}$		0.992	0.989	0.984	0.974	0.964	0.954	0.939	0.921	0.902	0.880	0.859
CFI		1.000	1.000	1.000	1.000	1.000	1.000	0.999	0.996	0.995	0.994	0.992
RMSEA		0.000	0.000	0.000	0.000	0.000	0.000	0.020	0.033	0.040	0.041	0.048
SRMR		0.029	0.033	0.037	0.043	0.047	0.050	0.054	0.056	0.059	0.064	0.065
'DUI internal' reliability		0.768	0.812	0.803	0.813	0.813	0.829	0.824	0.880	0.880	0.866	0.887
'DUI user-driven' reliability		0.792	0.728	0.791	0.807	0.811	0.811	0.812	0.811	0.826	0.827	0.826
'DUI external' reliability		0.845	0.845	0.729	0.846	0.847	0.847	0.824	0.727	0.848	0.816	0.818
'DUI internal' item count		4	5	5	5	5	6	6	8	8	8	9
'DUI user-driven' item count		3	3	3	4	5	5	5	5	6	6	6
'DUI external' item count		3	3	4	4	4	4	5	4	4	5	5
Possible combinations		3,072,300	8,295,210	16,105,320	24,460,128	30,261,924	30,988,140	26,586,696	19,336,632	11,424,438	5,373,840	1,878,528

Notes: "x" means that an item has been selected for inclusion in the short scale. Only the seed(s) with the best solution (i.e. highest $\varphi_{overall}$) are shown. Dashed lines separate the three DUI dimensions (see Table 2).

4.3 Additional exercises

To demonstrate the superiority of the results presented, we perform two additional methodological exercises that restrict the flexibility of the ACO. The first of these follows an approach that is often used in the psychometric literature (both within and beyond the ACO approach): we predefine the total length of the short scale, then we allocate the corresponding number of items across the identified factors using a proportional distribution rule. Specifically, we construct three short scales of fixed length comprising 10, 15 and 20 items respectively, and allocate the number of items per dimension proportionately to the original distribution of items across the three DUI dimensional factors identified in the EFA. To operationalize this, we calculate the proportion of items for each factor by dividing the number of unique items in each dimension (12 for "DUI internal", 7 for "DUI user-driven", and 9 for "DUI external") by the total number of retained items (28). We then multiply these proportions by the desired total scale length (10, 15, or 20). The resulting values are rounded to the nearest whole number, ensuring that each dimension is represented by at least three items in order to preserve factorial identification and content validity. This procedure ensures that each short scale reflects the relative conceptual weight of each dimension, thereby preserving the multidimensional integrity of the original measurement model. This fixed-length, proportionally balanced approach provides a complementary benchmark to the flexible ACO procedure, which is entirely data-driven. This allows us to compare heuristic allocation and algorithmic optimization in terms of statistical performance and conceptual interpretability.

Table 4 shows the optimal solution for each of the three predefined scale lengths, as determined by this proportional approach. Across all three short scale lengths (DUI-10, DUI-15, and DUI-20), six items are consistently selected. Conversely, none of the three items already identified in the flexible ACO procedure are ever selected in any of the derived scales (*Scope for trial-and-error learning*, *Monetary incentives for idea disclosure*, *Collaboration financing*). This persistent exclusion provides further evidence to support the main findings of Subsection 4.1, namely that the DUI mode cannot be captured statistically or conceptually using these items. Interestingly, the DUI-10 scale that performed best when subjected to the proportional constraint is identical to the DUI-10 scale obtained using the flexible ACO procedure reported earlier (see Tables 3 and 4). However, the constrained DUI-15 and DUI-20 scales differ from their flexible counterparts in that they exhibit lower values of $\varphi_{overall}$, indicating that imposing a fixed, proportional allocation of items across factors may limit the algorithm's ability to identify globally optimal configurations. Furthermore, closer inspection of the items selected to represent the "DUI user-driven" dimension reveals substantial variation between the DUI-10 scale and the longer scale versions (DUI-15 and DUI-20). This suggests that limited scale length may disproportionately affect the representation of this particular dimension. In contrast, the DUI-15 short scale is an almost perfect subset of the DUI-20 short scale: Thirteen out of the fifteen selected items for the DUI-15 scale are also selected for the DUI-20 scale, with the exceptions of *Maintaining good relations within the firm* and *Importance of network relations*, which are replaced by other items in the longer scale. Finally, in terms of robustness across optimization runs, the DUI-10 and DUI-20 solutions derived under the proportional constraint are each selected in only one out of five ACO runs. This limited recurrence indicates a certain degree of instability in the item selection process under fixed-length and proportionality conditions. In contrast, the flexible ACO procedure, which does not involve any predefined item allocations, produces a consistent DUI-20 scale across all five runs. This demonstrates the robustness and stability of the results obtained using the flexible ACO approach.

Although the CFA did not empirically support the further use of the finer-grained categorical structure originally proposed by Alhusen et al. (2021) (see Subsection 3.2), we revisit the intermediate category level in a second exercise. Here, we adopt the approach of ensuring good construct coverage by considering the underlying conceptual categories (Partsch et al., 2024). To this end, we modify the ACO algorithm to ensure that at least one item from each of the twelve categories is selected.[4] This approach aims to enhance the conceptual coverage of the DUI mode by ensuring that all categories are represented, even if they lack statistical validation as distinct latent factors. Applying this coverage constraint means that the minimum feasible length of the short scale is twelve items, i.e. one item per category. For longer scales, the algorithm can select additional items from any of the twelve categories. The results of this categorically constrained ACO procedure are summarized in Table 5. Interestingly, the short scales of lengths 16, 17, 19, and 20

[4]The number of categories is not 15, as in the original Alhusen et al. (2021) measurement framework. This is because the EFA reduced the number of items to 28 which removed three of the original subcategories completely.

derived under this construct-coverage constraint are identical to those generated by the flexible, flexible ACO algorithm. This indicates that, in these cases, the best-fitting item sets already include full categorical representation. This suggests that, when the scale length is sufficiently large, the flexible optimization naturally tends towards conceptually well-balanced solutions. Moreover, eight items are consistently selected across all scales, regardless of their length. This recurring set of items reinforces the robustness of these particular indicators and highlights their central role in capturing the multidimensional nature of DUI learning processes. As the length of the scale increases and more items can be selected, a disproportionate number of items from the "DUI user-driven" dimension are added. This indicates a higher degree of heterogeneity within this dimension and suggests that it encompasses more diverse, potentially less overlapping, learning activities compared to the other two DUI dimensions. At the category level, this heterogeneity is particularly evident in Category VII, where all three items are selected in the short scales ranging from 14 to 20. This indicates a high degree of variability and relevance within the category for broader construct coverage. In contrast, the "DUI external" dimension shows less variation: between four and five items from this dimension are selected across all scale lengths, implying a relatively higher level of homogeneity among the items and categories within this dimension. This consistency suggests that fewer items are required to adequately represent external interaction processes in the context of DUI learning. Taken together, these findings demonstrate that the category-based constraint can be integrated into the ACO optimization process without substantially compromising model fit or reliability, particularly for longer scales. Furthermore, this approach provides an additional layer of conceptual validation, ensuring that the breadth of the DUI innovation mode is preserved in short-form measurement instruments.

Table 4: Results of ACO with proportional distribution

	Survey item	DUI-10	DUI-15	DUI-20
DUI internal	Training regarding general qualification	x	x	x
	Scope for trial-and-error learning			
	Creativity in the workplace		x	x
	Maintaining informal contacts within the firm			x
	Maintaining good relations within the firm	x	x	
	Learning by observing			x
	Regular team meetings	x	x	x
	Knowledge exchange among employees with different tasks			x
	Open communication culture			x
	Delegation and degree of autonomy	x	x	x
	Monetary incentives for idea disclosure			
	Knowledge & idea management		x	x
DUI user-driven	Intensity & duration of customer contact		x	x
	Active request for feedback		x	x
	Use of customer support		x	x
	Organizational area of cooperation with customers		x	x
	Customized products	x		
	Additional or complementary products and services	x		x
	Customer involvement	x		
DUI external	Innovation cooperation within the sector	x	x	x
	Innovation cooperation across sectors	x	x	x
	Extra-industry relationship		x	x
	Innovation cooperation with consultancies/service providers	x		
	Relation with consultancies/service providers		x	x
	Collaboration financing			
	Importance of innovation awards			x
	Participation in network events			x
	Importance of network relations		x	
Random seed run (numbers from 1 to 5)		2	1, 2, 5	1
Optimization criteria				
$\varphi_{overall}$		0.992	0.947	0.846
CFI		1.000	0.999	0.992
RMSEA		0.000	0.015	0.047
SRMR		0.029	0.052	0.068
'DUI internal' reliability		0.768	0.824	0.887
'DUI user-driven' reliability		0.792	0.809	0.812
'DUI external' reliability		0.845	0.824	0.841
'DUI internal' item count		4	6	9
'DUI user-driven' item count		3	4	5
'DUI external' item count		3	5	6
Possible combinations		1,455,300	4,074,840	388.080

Notes: "x" means that an item has been selected for inclusion in the short scale. Only the seed(s) with the best solution (i.e. highest $\varphi_{overall}$) are shown. Dashed lines separate the three DUI dimensions (see Table 2).

Table 5: Results of ACO with category coverage

Dimension	Category	Survey item	DUI-12	DUI-13	DUI-14	DUI-15	DUI-16	DUI-17	DUI-18	DUI-19	DUI-20
DUI internal	I.	Training regarding general qualification	x	x	x	x	x	x	x	x	x
	II.	Scope for trial-and-error learning	x	x							
		Creativity in the workplace			x	x	x	x	x	x	x
	III.	Maintaining informal contacts within the firm								x	x
		Maintaining good relations within the firm	x	x	x	x	x	x	x		
		Learning by observing								x	x
	IV.	Regular team meetings		x	x	x	x	x	x	x	x
		Knowledge exchange among employees with different tasks	x					x	x		x
		Open communication culture						x	x	x	x
	V.	Delegation and degree of autonomy				x	x	x	x	x	x
		Monetary incentives for idea disclosure									
		Knowledge & idea management	x	x	x	x	x	x	x	x	x
DUI user-driven	VI.	Intensity & duration of customer contact	x	x	x	x	x	x	x	x	x
	VII.	Active request for feedback		x	x	x	x	x	x	x	x
		Use of customer support			x	x	x	x	x	x	x
		Organizational area of cooperation with customers	x	x	x	x	x	x	x	x	x
	VIII.	Customized products							x	x	x
		Additional or complementary products and services	x	x	x	x	x	x	x	x	x
		Customer involvement									
DUI external	IX.	Innovation cooperation within the sector	x	x	x	x	x	x	x	x	x
	X.	Innovation cooperation across sectors					x			x	x
		Extra-industry relationship	x	x	x	x	x	x	x	x	x
	XI.	Innovation cooperation with consultancies/service providers									
		Relation with consultancies/service providers	x	x	x	x	x	x	x	x	x
		Collaboration financing									
		Importance of innovation awards									
	XII.	Participation in network events								x	x
		Importance of network relations	x	x	x	x	x	x	x		
Random seed run (numbers from 1 to 5)			1,4	4	1,3,4	2,3	1,5	3	2,3,5	1,3,4,5	1,2,4,5
Optimization criteria											
$\varphi_{overall}$			0.938	0.959	0.955	0.950	0.939	0.921	0.898	0.880	0.859
CFI			0.999	1.000	1.000	1.000	0.999	0.996	0.994	0.994	0.992
RMSEA			0.013	0.000	0.000	0.005	0.020	0.033	0.040	0.041	0.048
SRMR			0.050	0.048	0.050	0.051	0.054	0.056	0.060	0.064	0.065
'DUI internal' reliability			0.807	0.796	0.787	0.824	0.824	0.880	0.880	0.866	0.887
'DUI user-driven' reliability			0.671	0.744	0.811	0.812	0.812	0.811	0.826	0.827	0.826
'DUI external' reliability			0.728	0.726	0.726	0.726	0.824	0.727	0.727	0.816	0.818
'DUI internal' item count			5	5	5	6	6	8	8	8	9
'DUI user-driven' item count			3	4	5	5	5	5	6	6	6
'DUI external' item count			4	4	4	4	5	4	4	5	5
Possible combinations			7,776	62,208	238,464	580,608	1,003,806	1,319,904	1,342,512	1,072,224	671,328

Notes: "x" means thst an item has been selected for inclusion in the short scale. Only the seed(s) with the best solution (i.e. highest $\varphi_{overall}$) are shown. Dashed lines separate the intermediate categories within the three DUI dimensions (see Table 2).

The results of the two additional exercises – namely the proportional item distribution and the enforced category coverage – corroborate the superiority of the data-driven, flexible ACO procedure presented in Table 3. For each specified scale length, the flexible ACO approach yields solutions of higher overall optimization quality, as indicated by higher $\varphi_{overall}$ values. Although the alternative strategies offer certain advantages, such as ensuring representational balance or conceptual construct breadth, this finding suggests that allowing the algorithm to select the DUI survey items based solely on statistical performance leads to short scales that are more conceptually and statistically robust and internally consistent.

5 Conclusion

This study lays the groundwork for future empirical research into measuring the Doing–Using–Interacting (DUI) mode of innovation, building on the conceptual framework developed by Alhusen et al. (2021) and its empirical translation in Reher et al. (2024b), who adapted it into a quantitative survey consisting of 40 measurement items. Drawing on their survey data collected from SMEs in Germany, we examine whether the three-dimensional structure of DUI mode learning, as theorized, can be observed empirically. Particular emphasis is placed on evaluating the suitability of individual DUI indicators and their contribution to the latent constructs underlying Alhusen et al.'s (2021) conceptual framework. An exploratory factor analysis confirms the tripartite conceptual division of DUI learning processes. However, a small subset of the observed indicators is found to be empirically inadequate due to low factor loadings or high cross-loadings. The three retained dimensions are labeled and interpreted as follows: 1. 'DUI internal', corresponding to learning-by-doing and internal interacting within the firm; 2. 'DUI user-driven', corresponding to learning-by-using with customers and users, and 3. 'DUI external', corresponding to learning through external interaction with other actors outside the firm.

The second contribution of this paper is based on this validated latent structure and lies in constructing short scales of varying lengths using Ant Colony Optimization (ACO). This objective is motivated by the fact that the original set of indicators conceptualized by Alhusen et al. (2021) and translated into concrete survey items by Reher et al. (2024b) is of limited practical use in typical innovation surveys due to its length and scope. Therefore, there is a need for short, valid scales that can accurately measure the various dimensions of the DUI mode despite their brevity. According to our optimization criteria it is shown that these short scales are best formed using an flexible ACO approach. The short scales derived serve as a first step towards developing practical measurement instruments for capturing the DUI mode in innovation surveys. Specifically, sets of 10—20 survey items (DUI-10 to DUI-20) have been constructed that fulfill the intended measurement purpose and can therefore be used as a basis for comparison and validation in future studies on the construction of DUI short scales. In this way, the present study also contributes to the broader discussion of how innovation in less R&D-intensive knowledge environments, such as those of small firms, low-tech sectors and lagging regions, can be better captured in the future using suitable innovation indicators.

A total of 12 survey items, formulated by Reher et al. (2024b), were excluded during the exploratory factor analysis due to a lack of meaningful loadings. Three of the 15 intermediate categories originally proposed by Alhusen et al. (2021) were thus omitted. Future research should investigate why this is the case, i.e. whether these categories are conceptually misaligned with DUI learning, whether the indicators proposed to measure them are inadequate, or whether adjustments should be made to their translation into survey questions. This could be crucial when examining the underlying measurement framework and/or refining the derived short scales in future studies on DUI mode learning.

Furthermore, while the short scales developed in this study are optimized for statistical performance within the current dataset, further testing and validation in independent samples and subsequent survey waves is required to evaluate their generalizability and external reliability (cf. Volz et al., 2021). This should be considered a central task for future research in this area. In particular, it is necessary to examine whether the derived short scales reliably reproduce the three-dimensional factor structure of the measurement framework proposed by Alhusen et al. (2021) when applied to different survey contexts. This approach mirrors the validation practices employed in personality psychology, where the factorial validity and measurement stability of the Big Five personality traits have been confirmed by evaluating multiple forms of short scales over the years (e.g., Rammstedt and John, 2007; Soto and John, 2017). Hence, future empirical studies should aim to collect large enough samples to enable rigorous testing of measurement invariance, i.e. whether the Alhusen et al. (2021) measurement framework applies to different subpopulations. In the context of innovation research, this would also involve testing for invariance between firms located in lagging regions and those in more developed regions (cf. Jankowsky et al., 2020; Partsch et al., 2024). Such analyses would not only enhance the robustness of the derived DUI short scales but also contribute to the emerging body of geographically contextualized innovation literature that emphasizes the relevance of spatial and institutional settings for innovation behavior beyond the narrow realm of in-house R&D.

Finally, another line of research could build on an interesting finding of the present study. It suggests that the short scales developed from DUI-13 onwards are more robust in terms of the consistency of their items than shorter scales (especially DUI-10 and DUI-12), which consist of different indicators. Further research is needed to confirm this conclusion, or to determine whether the explanation for the results lies elsewhere.

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Appendix

Table A.1: Descriptive statistics on the DUI indicators analysed

Measurement framework of Alhusen et al. (2021): 15 categories & 47 indicators	Respective survey questios used by Reher et al. (2024b)	Obs	Mean	Std. Dev.
LEARNING-BY-DOING-AND-INTERNAL-INTERACTING:				
I. Employed technology	Technological developments influence the learning processes in our company ...			
1. New technology introduction	- by introducing new technologies from outside (from other industries, companies, etc.) into our company.	429	3.177	1.381
2. Current technology improvement	- by technically improving existing machines and systems in the company.	429	2.755	1.448
II. Training	Regularly organized training courses strengthen our employees' knowledge and skills required for innovation activities ...			
3. Training regarding general qualification	- by imparting generally important qualifications that are also useful outside the company.	429	3.275	1.339
4. Training regarding firm-specific qualifications	- by imparting company-specific qualifications that can only be used for the company's tasks.	429	3.394	1.349
III. Trial-and-error learning	In order to explore new opportunities for innovation and improvement in our company ...			
5. Scope for trial-and-error learning	- we give our employees the freedom to learn by trial and error.	429	3.557	1.213
6. Use of experience	- we rely on our experience.	429	3.830	1.015
7. Creativity in the workplace	- we rely on the creativity of our employees.	429	3.751	1.142
IV. Informal contacts and firm-internal relations	To enable our employees to exchange knowledge and learn new things ...			
8. Maintaining informal contacts within the firm	- we support the cultivation of informal contacts within the company.	429	3.949	1.151
10. Maintaining good relations within the firm	- we support the establishment of exchange relationships within the company that promote innovation.	429	3.487	1.271
11. Learning by observing	- we support learning from experienced employees through observation and imitation.	429	3.916	1.185
V. Mechanisms of knowledge exchange	In order to support the exchange of experience among our employees ...			
12. Regular team meetings	- regular team meetings are held.	429	3.487	1.456
13. Knowledge exchange among employees with different tasks	- regular meetings are held between employees from different areas of responsibility on innovation-related issues.	429	3.366	1.409

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Table A.1 – *Continued from previous page*

Measurement framework of Alhusen et al. (2021): 15 categories & 47 indicators	Respective survey questios used by Reher et al. (2024b)	Obs	Mean	Std. Dev.
14. Open communication culture	- we promote a generally open communication and error culture.	429	4.161	1.136
VI. Human resource management tools	In order to strengthen the involvement of our company's employees in innovation projects ...			
15. Delegation and degree of autonomy	- employees are given their own decision-making powers and areas of responsibility.	429	3.916	1.179
17. Monetary incentives for idea disclosure	- we rely on tangible and intangible incentives for employees to contribute ideas and develop innovations.	429	3.044	1.376
18.+19. Knowledge & idea management	- we rely on organizational measures for the efficient use of existing know-how (knowledge management, suggestion scheme, etc.).	429	3.275	1.249
LEARNING-BY-USING:				
VII. Cooperation with customers	Our cooperative relationships with customers ...			
20.+22.+23. Competent customers	- focus on innovation-oriented customers who are particularly competent in our field of business.	429	2.853	1.391
21.+24. Intensity & duration of customer contact	- are intensive, based on trust and as long-term as possible.	429	4.287	1.059
VIII. Customer contact	In order to give our customers the opportunity to influence innovations and improvements to the company as part of customer contact ...			
25. Organizational area of cooperation with customers	- we ensure internally that customer knowledge reaches the relevant places in the company.	429	3.783	1.216
26. Active request for feedback	- we actively ask them for feedback on their experiences of using new products/services.	429	3.224	1.442
27. Use of customer support	- we use the personal exchange during customer support.	429	3.923	1.235
28. Use of social media	- we make use of social media.	429	2.450	1.473
IX. Product specification	In order to satisfy our customers in terms of product specification ...			
29. Customized products	- we develop products or services that are specifically adapted to the wishes and needs of individual customers.	429	3.636	1.420
30.+31. Additional or complementary products and services	- we offer additional or complementary products/services.	429	3.513	1.361
32. Customer involvement	- we involve the customer in the development and adaptation of products/services.	429	3.245	1.470
LEARNING-BY-EXTERNAL-INTERACTING:				
X. Interaction with suppliers	When we work with our suppliers or subcontractors, we focus on ...			

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Table A.1 – *Continued from previous page*

Measurement framework of Alhusen et al. (2021): 15 categories & 47 indicators	Respective survey questios used by Reher et al. (2024b)	Obs	Mean	Std. Dev.
33. Innovation cooperation with suppliers	- cooperation in the area of innovation.	429	2.928	1.345
34. Suppliers' competences	- learning from their expertise in order to obtain innovation-relevant information on new materials, processes, etc.	429	3.345	1.366
35. Supplier relationship	- a close relationship based on trust.	429	4.219	1.065
XI. Interaction with competitors	As part of our innovation activities, we benefit from our competitors ...			
36. Competitor relationship	- by learning from their successes and failures.	429	3.478	1.291
37. Competitive pressure	- in that we have an incentive to innovate due to the mutual competitive relationship.	429	2.998	1.365
XII. Interaction with intra-sectoral firms	As part of our innovation activities, we benefit from other companies in our industry ...			
38. Innovation cooperation within the sector	- by maintaining an innovation cooperation with them.	429	2.184	1.321
39. Intra-sectoral relationship	- by maintaining a close and trusting relationship.	429	2.930	1.382
XIII. Interaction with extra-sectoral firms	As part of our innovation activities, we benefit from companies from other sectors ...			
40. Innovation cooperation across sectors	- by maintaining an innovation cooperation with them.	429	2.177	1.308
41. Extra-industry relationship	- by maintaining a close and trusting relationship.	429	2.762	1.421
XIV. Interaction with consultancies and service providers	As part of our innovation activities, we benefit from consulting firms and other public and non-public service providers ...			
42. Innovation cooperation with consultancies/service providers	- by maintaining an innovation cooperation with them.	429	1.949	1.259
43. Relation with consultancies/service providers	- by maintaining a close and trusting relationship.	429	2.322	1.443
44. Collaboration financing	- by gaining better access to external funding.	429	1.814	1.203
45. Importance of innovation awards	- by achieving greater visibility by participating in innovation award ceremonies.	429	1.541	0.998
XV. Trade associations and networks	As part of our innovation activities, we benefit from trade associations, chambers and networks ...			
46. Participation in network events	- by participating in networking events to gain access to new external knowledge.	429	2.716	1.445
47. Importance of network relations	- by maintaining good relationships and regular interactions with our network partners.	429	2.774	1.432

Table A.2: CFA

Fit statistic	
Likelihood ratio	
chi2_ms(737)	3458.457
p >chi2	0.000
chi2_bs(780)	9129.839
p >chi2	0.000
Population error	
RMSEA	0.093
90% CI, lower bound	0.090
upper bound	0.096
pclose	0.000
Information criteria	
AIC	52056.284
BIC	52555.844
Baseline comparison	
CFI	0.674
TLI	0.655
Size of residuals	
SRMR	0.083
CD	0.997

Figure A.1: Scree plot of eigenvalues after EFA