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TEAMS AS LEARNING SQUADS: failing fast, smart, and together

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ABSTRACT

Errors and failures in the organizational setting are often associated with non-conforming behavior, something that should be avoided, and that often requires some sort of correction and mitigation. Moreover, employees are expected to demonstrate innovative working behaviors by producing and/or supporting the creation and generation of new ideas to solve existing organizational gaps or to create new opportunities. Therefore, the present study investigates the relationship between organizational learning from errors, absorptive capacity, and innovative work behavior. Survey data from 86 participants were collected using convenience sampling through posts made on professional social media. Data analysis was performed using Partial Least Squares – Path Modeling and the results showed that absorptive capacity is more important to innovative work behaviors than organizational learning from errors. At the end of the study, limitations and recommendations for further studies are outlined.

Keywords: Learning from Errors/Failures. Organizational Learning. Innovation. Innovative working behavior.

1 INTRODUCTION

As the pandemic stroked our society creating an unprecedented crisis, both humanitarian and economic, organizations were compelled to rethink the workplace and the way through which value is created. Increasing uncertainty and the need to keep pace with an evolving business operation are ingredients for a new working dynamic where disruption becomes the new normal.

Additionally, fierce competition for resources and target markets is forcing companies to strive for increasing levels of flexibility, agility, learning, and innovation. Powered by unlimited creativity, companies must rely on resources outside their boundaries and capacities (Wang, 2021) to anticipate innovation trends and appropriate emerging ideas before the competitors can recognize them (W. M. Cohen & Levinthal, 1994). The organizational ability to identify, access, curate, and assimilate external knowledge into organizational processes and routines is referred to as absorptive capacity (W. M. Cohen & Levinthal, 1990).

Besides, innovation is typically considered a differentiation factor and an important determinant of company growth (Helkkula et al., 2018), especially in turbulent times or crises such as COVID-19 (Heinonen & Strandvik, 2021) and strong competitive pressure from technology and globalization (Patrício et al., 2018). Nevertheless, innovation is a risky venture, naturally prone to errors and embedded in ambiguity, requiring from individuals an experimentation mindset and favored conditions where exploration and learning thrive (Hartley & Knell, 2021).

Occurs that errors or failures are often associated with non-conforming behaviors, losses, and negative consequences, that need to be avoided and usually require some sort of correction and mitigation (Leoncini, 2016; Zhao & Olivera, 2016). However, in fast-changing environments where the ability to adapt and innovate can modify the rules of the competition and give companies a strategic advantage, companies that can deal with uncertainty and operate in situations of ambiguity and little information would be better positioned (Argote & Miron-Spektor, 2011). Thus, companies that can reframe errors as learning opportunities have the potential to create a context where individuals are more creative (Cannon & Edmondson, 2005; Wilhelm et al., 2019).

In this context, organizational learning, in general, and more specific learning from errors, is of great relevance as it aims to understand the factors, processes, and motivations related to the learning of new skills and knowledge vis-à-vis the context in which it occurs. However, much of this learning results from informal strategies (Ushiro & Bido, 2016) that stem from experiences lived inside and outside organizations and that thrive in a psychologically safe environment (Edmondson, 1999) where individuals engage and cooperate in learning actions. Therefore, organizational learning from error refers to the intentional, manageable, and risky process in which individuals use trial and error to take ownership of what works best for an intended.

Furthermore, innovative working behavior consists of the individual action toward the exploration of possibilities or the identification of problems, combined with the generation of ideas and coalitions necessary to implement a solution or create a product/service (De Jong & Den Hartog, 2010). It is triggered by the individual, but it turns out to be a group activity when externalization, coalitions, and implementation of the ideas are necessary.

Concerning specifically team level, learning and innovative work behavior are mutually dependent on information sharing, team reflection, and team activity (Widmann et al., 2016). Therefore, we argued that both, learning from errors and innovative behaviors share the need for experimentation, as well as the necessity for a safe and sound context of cooperation and emotional support, where teams work and share values such as respect and trust.

Nevertheless, much emphasis has been placed on studying innovative work behavior and learning from errors at the individual level (Widmann et al., 2016), neglecting the social nature of these processes and the interdependencies among individuals for emotional support, knowledge sharing, trust, and psychological safety. Team psychological safety refers to "a shared belief that the team is safe for interpersonal risk-taking" (Edmondson, 1999, p. 352).

Consequently, the research problem proposed is to **understand the relationship between organizational learning from errors, absorptive capacity, and innovative working behaviors in team settings**. Therefore, by exploring the contribution of organizational capabilities related to team learning, here limited to learning from errors mechanism, the present study aims to contribute to the broader literature on organizational learning and innovation, as well as to provide insights to practitioners on how to facilitate the creation of team settings where learning and innovative behaviors flourish.

To reach the objectives previously expressed, the study relies on a quantitative descriptive method where working teams within organizations will be used as the level of analysis.

2 THEORETICAL FRAMEWORK

This session is formed by the theories supporting the choices of construct, as well as its definitions and relevant data for the proposed research framework.

2.1 Innovative Work Behavior (IWB)

Innovative work behavior (IWB) is commonly associated with the individual action of creating ideas as well as their implementation or the support necessary for them (De Jong & Den Hartog, 2010). However, although individual employees play an important role in triggering the initial exploration and the idea generation, the development of innovation is a social process, forged through interactions of multiple actors sharing problems, and ideas, eventually mobilizing resources to realize the ones selected (Widmann et al., 2016).

According to De Jong and Den Hartog (2010), it is necessary to make a distinction between creativity and IWB in the sense that the former is concerned about ideation which is pretty much dependent on the individual cognitive processes, whilst the latter includes the necessary buy-in from peers (team) and coalition for implementation of the ideas, i.e. ensuring the benefits of solving a gap or a problem in materialized as an output.

Moreover, a common trace of the creative and entrepreneurship literature is that before ideas are generated, there is a stage of exploration, where gaps and problems are identified, and these are distinct behaviors. Conversely, before bringing ideas to life, a sponsor is needed, someone able to articulate how the idea solves the identified gap/problem. In that sense, championing is about building coalitions, a shared understanding that mobilizes action and although regarded as resulting from individual action, is also embedded in social relationships and emotions that can range from enthusiasm to resistance (De Jong & Den Hartog, 2010).

According to Widmann et al. (2016), the social nature of the innovative work behavior implies that teams are the organizational structure closer to individuals and where the innovation development happens. Certain behaviors in teams can foster or constrain innovations, whereas team reflection, open communication, and a supportive climate can be antecedents for ideation, development, and implementation of innovative ideas.

Thus, IWB requires the engagement of employees in work activities that are not necessarily linear, mixing physical and cognitive actions, that vary from exploration of gaps or the identification of problems, the generation of possible ideas and solutions, championing and have the buy-in of other organizational members, and the implementation of the selected ideas (De Jong & Den Hartog, 2010; Widmann et al., 2016). Widmann et al. (2016) assert that according to the work context, the activities necessary to realize the ideas are shared among different team members.

We draw from Widmann et al. (2016, p. 432) the definition of innovative work behavior as “the sum of all physical and cognitive work activities teams carry out in their work context to attain the necessary requirements for the development of an innovation”. The definition clearly articulates the option for a team perspective where the involvement of multiple actors is inevitable.

2.2 Organizational Learning from Error (OLE)

Common sense suggests that failures in business are negative events and should be avoided as much as possible (Leoncini, 2016; Wilhelm et al., 2019). According to Argyris (1977), in its essence, organizational learning is a process of detecting and correcting errors. Besides, learning from failures is not as natural as people may initially consider requiring individual diligence and an organizational environment where this type of learning can take place and drive innovative activity (Watkins & Bazerman, 2003). Accordingly, as innovative activity is inherently uncertain and prone to failure (Leoncini, 2016), companies must absorb and critically learn from innovation attempts.

Thus, instead of working against errors and fearing them, a better idea is “putting intelligent failure to work” (McGrath, 2011, p. 83), by reframing it using a critical view of why the effort did not produce the expected outcomes, and what new things were learned along the way (Tahirsylaj, 2012). Hence, the very few organizations that succeed in reinterpreting errors, by incentivizing their employees towards innovation and creative behaviors are the ones where errors enhance “the likelihood of drawing the right ideas out of someone else’s failure” (Leoncini, 2016, p. 99). Authors such as Argote and Miron-Spektor (2011) stated that learning from failure is key for individual performance and sustainable organizational success.

In this work, we draw from the work of Leoncini (2016) the definition of error or failure, here used interchangeably. For this author, failure is the result of a mismatch between the result and the expectation. One that wants to learn from error must develop a strong capacity for tracing back and revisiting, reflecting, on the process that failed. Therefore, by learning from failure we understand what caused the mismatch in expectation and this newly created knowledge is effective in driving innovative behavior (Leoncini, 2016).

However, this is easier said than done. Some scholars argued that error experience can be so painful that defensive reactions occur and feelings such as shame and fault are common (Edmondson, 2012). The author also stated that the experience of failure is inherently social so learning from errors would fault short in explanation if we just considered the individual experience in isolation (Wilhelm et al., 2019).

This article departs from the perspective that learning in the organizational setting is a process and a social endeavor that takes place on different levels, from the individual and group to the organizational sphere (Pérez López et al., 2005). The authors argued that as an interdependent process, organizational learning requires coordination of the underlined stages, a shared purpose that gives sense and direction to activities. Furthermore, as a social endeavor, learning takes place in the presence of social relations, where emotions and perceptions can foster or stifle learning (Watzek et al., 2019; Wilhelm et al., 2019).

Besides, learning from errors is embedded in an emotional context where employees would be more inclined to learn from their failure experiences when medium to high levels of psychological safety is present in the working group (Wilhelm et al., 2019). Psychological safety happens to occur in the “immediate social context in which employees are typically embedded in contemporary organizations” (Wilhelm et al., 2019, p. 5), that is, the working group or team where the employee performs the predominant part of his/her work. Psychological safety refers to “a shared belief that the team is safe for interpersonal risk-taking” (Edmondson, 1999, p. 352).

As an analogy, we may think in terms of voltage. It is the difference in potential between two points, that establishes the flow of charges (current). In the organizational setting, it is the difference between the expected and the actual result of an action or experiment that triggers the learning. The immediate social context is the conduit that can facilitate or even block learning from happening.

This metaphor is consistent with the work of Bontis et al. (2002), where organizational learning is a dynamic process where learning occurs over time, within and across levels, in a flow. Learning within a level is related to what the authors called stock and the one that occurs between levels as a flow (feed-forward and feed-back). Bontis et al. (2002) argued that individuals use their intuition and interpretation to make sense of changes and opportunities as the ignition of this dynamic process.

Hypothesis 1: Organizational learning from errors influences positively innovative work behavior in teams.

2.3 Absorptive Capacity (ACAP)

Absorptive capacity (ACAP) refers to the firm’s ability to identify, access, incorporate, transform, and apply new ideas and external knowledge into an organization’s process (W. M. Cohen & Levinthal, 1990). Thus, according to these authors, before absorbing knowledge, organizations need the capability to recognize the value of the new knowledge and drive it toward a commercial end. Moreover, the ability to recognize external knowledge requires prior knowledge, and to make sense of the value of this information (Todorova & Durisin, 2007). That way, ACAP is a construct often used in research that explores collaborative strategies between different organizations (Dyer & Singh, 1998), which makes ACAP suitable for studying the relationship between value co-creation and service innovation.

Yet, despite a critical mass of research that draws upon absorptive capacity, there has been no comprehensive assessment of the role of this construct as a mediator of value co-creation in the digital service ecosystem. Furthermore, prior studies as inherently biased toward the exploitation of existing knowledge (Roberts et al., 2012), whereas this study investigates how the ACAP facilitates the exploration of new ideas and experiences created conjointly with partners and customers.

Besides, as absorptive capacity depends on prior knowledge to be able to assess value and incorporate it, an indicator of success in transforming the new ideas into effective commercial use can be the number of ideas and projects that result in new offers (Zahra & George, 2002). On the other hand, literature shows that digital-enabled companies are said to improve their absorptive capabilities through learning-by-doing (Sambamurthy et al., 2003). This rationale makes us argue that an organization able to draw information from customers and partners to create new ideas, as well as learn what works or not, will be better equipped to innovate. So, the following hypothesis was formulated.

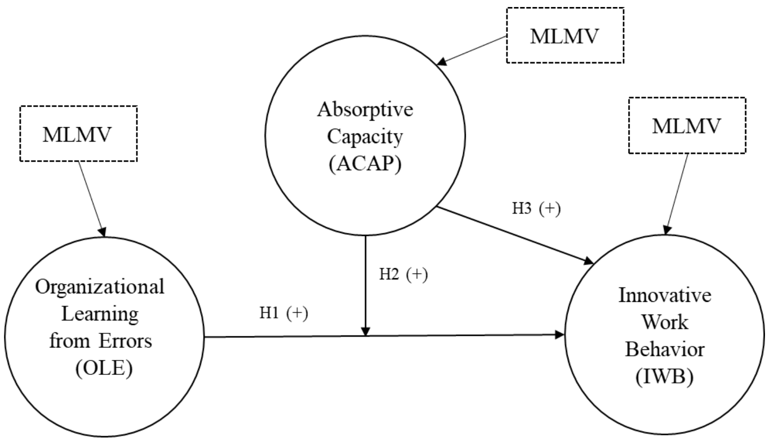
Hypothesis 2: The absorptive capacity strengthens the relationship between organizational learning from error and innovative work behavior in teams.

Hypothesis 3: The absorptive capacity influences positively innovative work behavior in teams.

2.4 Theoretical Model

Figure 1 depicts the conceptual model and captures the constructs used and the hypothesis that will be investigated.

Figure 1 - Theoretical Model



Source: from authors.

Legend: MLMV is a measured latent marker variable used to control de common method bias.

3 METHOD

This study relies on a deductive method (Sekaran & Bougie, 2016) to explore the relationship between organizational learning from errors and innovative work behavior. It draws from the perspective that both, organizational learning from errors and innovative work behaviors are social activities and are facilitated in team contexts (Wilhelm et al., 2019). Therefore, teams are the level of analysis used and for the present study, a team consists of at least three team members who interact to accomplish common goals and perform relevant tasks to the organizations they belong to. The data was obtained through an online survey.

3.1 Sample

To understand the relationship between organizational learning from errors and innovative work behavior, data from employees working in private companies in different domains will be used. To acquire the data, a convenience sampling approach through professional social media (Linkedin) was used to collect data with a structured questionnaire filled in online, between May 30th and July 06th, 2022. The sample accounted for 91 responses, where 90 were considered valid.

The software G*Power 3.1 was used for the Power analysis (Erdfelder et al., 2009), and the values recommended by Hair et al. (2014, p. 11) were used: two tails, with a significance level of 5%, and a power level of 80%. Assuming 3 predictors were used, the minimum sample size estimated a priori is 77 cases. Thus the sample size provides the minimum statistical significance.

3.2 Measurement

The survey instrument was built on established constructs, and except for demographic measures, all other measures used a Likert-type response scale and are reflectively specified (Jarvis et al., 2003).

The construct **Organizational Learning from Errors (OLE)** was operationalized using the scale proposed by Putz et al. (2013). Furthermore, the construct **Absorptive Capacity (ACAP)** as a multidimensional construct (Roberts et al., 2012) and a multi-item scale was drawn from Flatten et al. (2011), where four dimensions were used as reflective second-order constructs as defined by Zahra and George (2002). The ACAP is framed as dynamic capability aligned with IS research (Roberts et al., 2012) and will be measured by 14 items that cover: (a) three items for the acquisition; (b) four items in the assimilation; (c) four items in transformation; (d) three items in the exploitation dimension.

The scale for the dependent variable, **Innovative Work Behavior (IWB)** was derived from the work of Messmann and Mulder (2020) that measured IWB with a short and unidimensional instrument. The scale proposed by Messmann and Mulder is simpler than the well-accepted instrument proposed by De Jong & Den Hartog (2010) that measures the construct in terms of four dimensions: (1) exploration; (2) generation; (3) championing; and (4) implementation.

Common method variance (CMV)

When responses in a survey collect information for both, independent and dependent variables in the same format at the same point in time, chances are to either overestimate or underestimate the effect of phenomena (Podsakoff et al., 2003). This effect is known as common method variance (CMV). In short, CMV is the ‘‘variance that is attributable to the measurement method rather than to the constructs the measures represent’’(Podsakoff et al., 2003, p. 879).

To overcome that extraneous effect, this study relies on measuring latent marker variable (MLMV) as a mechanism to detect and correct for CMV (Chin et al., 2012). Hence, the MLMV approach consists in collecting together with the original survey, multiple unrelated measures that have no nomological relationship with constructs under investigation, and using the same survey and scale (Chin et al., 2012). Following the recommendations made by these authors, the method will be implemented using 2 additional items per construct being measured. They will be placed alongside regular questions to minimize the effects of respondent fatigue and response pattern. Appendix 4 presents the proposed scale for the MLMV construct.

3.3 Procedures

An initial pre-test was performed to assess if the measurement instrument was clear and if items in the scale were comprehensive concerning the response format (face validity). In practical terms face validity is related to how the respondents see the measure i.r.t. to what is being measured, while content validity is also concerned about what the authors believe is being measured (Netemeyer et al., 2003). All the items of an instrument, the response formats, the number of scale points, and instructions to the respondent all should be judged for representativeness. By performing the pre-test, we can see the struggles the respondent faces and collect their feedback about how difficult/easy was to respond to the instrument. The Portuguese version of the instrument was reviewed by one of the authors and two independent researchers and adjustments were made to cope with Brazilian reality and language.

3.4 Analysis

The following data preparation steps were followed before the analysis: 1) data encoding: categorical variables such as Gender were encoded, where Male was designated as "1" and Female as "0"; 2) Except by one case (case #3 had all responses as blank and was one of the pre-tests made just for face validity) all other responses were considered valid, totalizing 90 valid cases; 3) 13 missing values were identified, from those 12 had averages inputted, the remaining item was a text item and was left untouched; 4) finally, the item OLE_GC2.R was a reverse indicator, and the responses were inverted to reflect the characteristic (1→6, 2→5, 3→4, 4→3, 5→2, 6→1).

To estimate the relationship between OLE, ACAP, and IWB, a structural equation model was evaluated using the Partial Least Square (PLS) considering the following assumptions: data is not normally distributed; the sample size is small for using with covariance models, and PLS would allow comparability with previous studies.

4 RESULTS

In this section, the results of descriptive statistics, the evaluation of the measurement model (validity and reliability of the constructs), and the assessment of the structural model are presented.

4.1 Demographic data

Demographic data in the sample collected shows that 77% of the respondents (69 participants) are males, also 64% of the respondents is in the age group between 25 and 44 years old and the sample included people from different hierarchical levels, as shown in Table 1.

Table 1 – Respondent Profile

Demographic Variables		Sample	Frequency
Genre	Male	69	77%
	Female	21	23%
Age Group	18-24 years	8	9%
	25-34 years	30	33%
	35-44 years	28	31%
	45-54 years	13	14%
	55-64 years	11	12%
Education	High school graduate or equivalent	2	2%
	Bachelor's Degree	51	57%
	Master's Degree	30	33%
	Ph.D. or higher	7	8%
Job position	Senior Management	18	20%
	Middle Management	22	24%
	Non-Management Technical/Professional	45	50%
	Others	4	4%
	Missing	1	1%
Workgroup Size	1-5 people	28	31%
	6-10 people	41	46%
	11-20 people	9	10%
	More than 20 people	12	13%

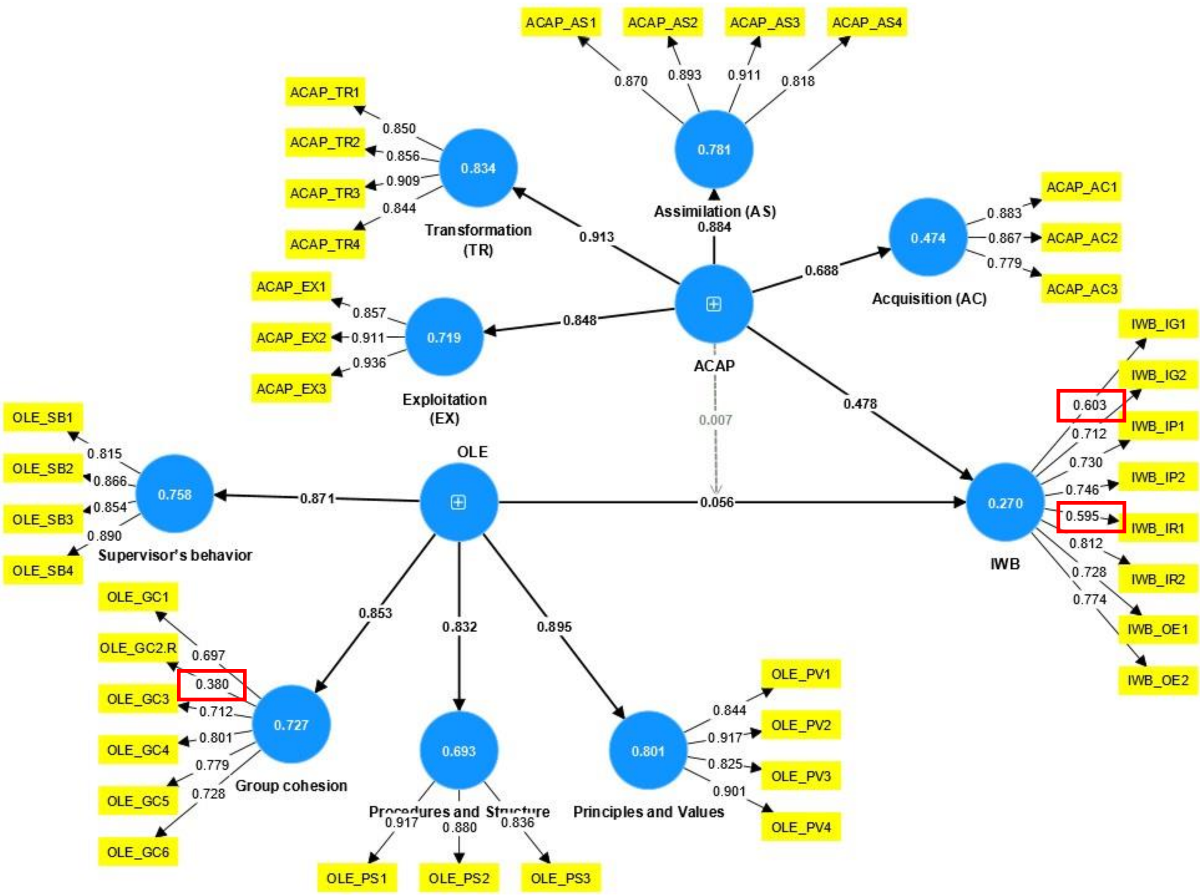
Source: from authors.

4.2 Assessing the Measurement Model

PLS-SEM is a causal modeling approach aimed at maximizing the explained variance of the dependent latent constructs (Joe F. Hair et al., 2011). PLS-SEM assessment typically follows a two-step approach: 1) assessments of the measurement models; 2) assessment of the structural model. The former examines the measures' reliability and validity according to certain criteria associated with formative and reflective measurement model specification (Joe F. Hair et al., 2011). The latter involves the assessment of the structural model estimates.

To verify the consistency reliability and convergent validity, a first run was made using all dimensions as predicted by the theoretical model used. Additionally, all items related to Absorptive Capacity and Organizational Learning from Errors were grouped under second-order constructs – a multidimensional constructs created as an abstraction for first-order construct (Joseph F. Hair, Hult, et al., 2014) – called "ACAP" and "OLE", respectively, as depicted in Figure 2. The PLS algorithm was run using default values for initial weight; factor weighting was defined as "Path", which is the recommended approach (Joseph F. Hair, Hult, et al., 2014).

Figure 2 – Original Structural Model



Source: from authors.

According to Joseph F. Hair, Hult, et al., (2014), composite reliability is a better measure of internal consistency than Cronbach's alpha and was used in this study. Furthermore, Chin & Newsted (1999) suggested the construct is said to have internal consistency when its composite reliability is higher than 0.70. For convergent validity, the Average Variance Extracted (AVE) is used to understand if a single factor is responsible for more than 0.50 of the extracted variance (Joe F. Hair et al., 2011). The AVE should be higher than 0.50 for convergent validity. Thus, the item(s) marked in red, see Table 2 are the one(s) that fall out of the referred criterion and need further investigation.

Table 2 – Original Model - Construct reliability and validity

	Cronbach's alpha	rho_A	Composite reliability	Average variance extracted (AVE)
ACAP	0.934	0.938	0.903	0.702
Acquisition (AC)	0.799	0.821	0.881	0.713
Assimilation (AS)	0.896	0.897	0.928	0.763
Exploitation_(EX)	0.884	0.888	0.929	0.813
Group cohesion	0.782	0.816	0.845	**0.486**
IWB	0.865	0.899	0.893	0.512
OLE	0.937	0.941	0.921	0.745
Principles and Values	0.895	0.905	0.927	0.761
Procedures and Structure	0.85	0.851	0.91	0.771
Supervisor's behavior	0.879	0.879	0.917	0.734
Transformation_(TR)	0.888	0.889	0.922	0.749

Source: from authors.

To increase convergent validity, indicators where the outer loading is less than 0.70 (Joseph F. Hair, Black, et al., 2014) become candidates for removal from the model. Therefore, the indicator "OLE_GC2.R" from "Group Cohesion" was removed. This is a reverse response indicator that explores the effect of competition among peers affects the discussion of errors. The data suggested the indicator is not relevant for measuring Group Cohesion. The resulting model was named "Model_1" and was reassessed as shown in Table 3.

Table 3 –Model_1 - Construct reliability and validity

	Cronbach's alpha	rho_A	Composite reliability	Average variance extracted (AVE)
ACAP	0.934	0.938	0.903	0.702
Acquisition (AC)	0.799	0.821	0.881	0.713
Assimilation (AS)	0.896	0.897	0.928	0.763
Exploitation_(EX)	0.884	0.888	0.929	0.813
Group cohesion	0.802	0.809	0.863	0.558
IWB	0.865	0.899	0.893	0.512
OLE	0.937	0.941	0.922	0.747
Principles and Values	0.895	0.905	0.927	0.761
Procedures and Structure	0.85	0.851	0.91	0.771
Supervisor's behavior	0.879	0.879	0.917	0.734
Transformation_(TR)	0.888	0.889	0.922	0.749

Source: from authors.

Next, the discriminant validity was evaluated. According to Joseph F. Hair, Hult, et al. (2014, p. 104), discriminant validity refers "to the extent to a which a construct is truly distinct from other constructs by empirical standards". Joe F. Hair et al. (2011) suggest the following criterion for validating discriminant validity:

- The AVE of each latent construct should be higher than the construct's highest squared correlation with any other latent construct (Fornell–Larcker criterion).
- An indicator's loadings should be higher than all of its cross-loadings.

To determine the discriminant validity, it is necessary to calculate the correlation matrix between 1st order constructs. Table 4 captures the referred matrix:

Table 4 –Model_1 - First-order correlation matrix

	1	2	3	4	5	6	7	8	9
1- Acquisition (AC)	**0.844**								
2- Assimilation (AS)	0.471	**0.874**							
3- Exploitation_(EX)	0.409	0.699	**0.902**						
4- Group cohesion	0.368	0.486	0.564	**0.747**					
5- IWB	0.477	0.408	0.457	0.386	**0.716**				
6- Principles and Values	0.459	0.642	0.689	0.707	0.348	**0.872**			
7 - Procedures and Structure	0.445	0.639	0.495	0.607	0.406	0.671	**0.878**		
8- Supervisor's behavior	0.509	0.619	0.572	0.652	0.336	0.686	0.661	**0.857**	
9 - Transformation_(TR)	0.595	0.710	0.707	0.611	0.439	0.687	0.568	0.579	**0.865**
Composite Reliability	0.881	0.928	0.929	0.863	0.893	0.927	0.910	0.917	0.922
Average Variance Extracted (AVE)	0.713	0.763	0.813	0.558	0.512	0.761	0.771	0.734	0.749

Source: from authors.

Discriminant validity is supported since all items on the diagonal are greater than the other correlations for the same construct (Joe F. Hair et al., 2011). Furthermore, Table 5 captures the discriminant validity considering the 2nd order construct related to OLE and ACAP. To calculate it we eliminate the subdimensions of OLE and ACAP in favor of the 2nd order constructs and reassessed the composite reliability and the average variance extracted according to the number of sub-items and their respective loads.

Table 5 –Model_1 - Second-order correlation matrix

	1	2	3
1- ACAP	**0.838**		
2- IWB	0.519	**0.716**	
3- OLE	0.779	0.425	**0.865**
Composite Reliability	0.903	0.893	0.922
Average Variance Extracted (AVE)	0.702	0.512	0.747

Source: from authors.

The result shows that discriminant validity is supported for first and second order constructs since the AVE values on the diagonal are greater than the correlation coefficients of other constructs. Furthermore, when the analysis is performed on the indicator level, the discriminant validity is also supported:

Table 6 –Model_1 - Cross Loading Matrix

	Acquisition (AC)	Assimilation (AS)	Exploitation_(EX)	Transformation_(TR)	IWB	Group cohesion	Procedures and Structure	Principles and Values	Supervisor's behavior
ACAP_AC1	**0.883**	0.477	0.382	0.590	0.381	0.376	0.449	0.443	0.458
ACAP_AC2	**0.867**	0.412	0.375	0.491	0.420	0.369	0.412	0.471	0.543
ACAP_AC3	**0.779**	0.277	0.263	0.405	0.418	0.154	0.236	0.213	0.256
ACAP_AS1	0.453	**0.870**	0.660	0.607	0.369	0.448	0.610	0.614	0.534
ACAP_AS2	0.439	**0.893**	0.593	0.634	0.420	0.484	0.522	0.531	0.568
ACAP_AS3	0.381	**0.911**	0.616	0.627	0.333	0.401	0.571	0.526	0.559
ACAP_AS4	0.368	**0.818**	0.572	0.614	0.301	0.361	0.527	0.573	0.501
ACAP_EX1	0.386	0.594	**0.857**	0.615	0.372	0.579	0.488	0.656	0.582
ACAP_EX2	0.352	0.608	**0.911**	0.627	0.452	0.440	0.352	0.579	0.468
ACAP_EX3	0.369	0.686	**0.936**	0.670	0.413	0.510	0.496	0.630	0.501
ACAP_TR1	0.568	0.670	0.659	**0.850**	0.472	0.485	0.484	0.631	0.478
ACAP_TR2	0.472	0.581	0.535	**0.856**	0.362	0.465	0.549	0.574	0.459
ACAP_TR3	0.508	0.631	0.598	**0.909**	0.329	0.595	0.521	0.620	0.540
ACAP_TR4	0.506	0.570	0.650	**0.844**	0.350	0.568	0.412	0.547	0.524
IWB_IG1	0.149	0.141	0.197	0.099	**0.603**	0.146	0.155	0.050	0.180
IWB_IG2	0.342	0.315	0.314	0.358	**0.712**	0.372	0.434	0.329	0.301
IWB_IP1	0.221	0.195	0.201	0.291	**0.730**	0.207	0.198	0.150	0.199
IWB_IP2	0.452	0.249	0.355	0.321	**0.746**	0.310	0.251	0.339	0.253
IWB_IR1	0.150	0.242	0.259	0.123	**0.595**	0.295	0.173	0.167	0.097
IWB_IR2	0.405	0.462	0.538	0.466	**0.812**	0.373	0.390	0.328	0.406
IWB_OE1	0.326	0.204	0.285	0.299	**0.728**	0.208	0.227	0.217	0.126
IWB_OE2	0.481	0.352	0.290	0.333	**0.774**	0.205	0.333	0.239	0.209
OLE_GC1	0.203	0.262	0.313	0.413	0.250	**0.697**	0.313	0.396	0.469
OLE_GC3	0.237	0.177	0.316	0.342	0.081	**0.709**	0.321	0.428	0.459
OLE_GC4	0.197	0.299	0.410	0.440	0.213	**0.795**	0.476	0.556	0.441
OLE_GC5	0.291	0.491	0.447	0.491	0.403	**0.786**	0.517	0.592	0.470
OLE_GC6	0.415	0.521	0.573	0.563	0.436	**0.742**	0.582	0.622	0.584
OLE_PS1	0.438	0.606	0.465	0.539	0.403	0.538	**0.917**	0.571	0.596
OLE_PS2	0.441	0.554	0.395	0.523	0.373	0.582	**0.880**	0.580	0.563
OLE_PS3	0.290	0.520	0.443	0.432	0.289	0.476	**0.836**	0.616	0.583
OLE_PV1	0.337	0.513	0.539	0.566	0.374	0.652	0.602	**0.844**	0.504
OLE_PV2	0.382	0.606	0.625	0.610	0.289	0.684	0.692	**0.917**	0.625
OLE_PV3	0.347	0.483	0.546	0.517	0.170	0.467	0.379	**0.825**	0.558
OLE_PV4	0.524	0.622	0.683	0.690	0.364	0.641	0.631	**0.901**	0.695
OLE_SB1	0.550	0.681	0.542	0.571	0.511	0.581	0.756	0.563	**0.815**
OLE_SB2	0.416	0.391	0.458	0.494	0.233	0.580	0.493	0.546	**0.866**
OLE_SB3	0.372	0.454	0.441	0.463	0.157	0.549	0.491	0.626	**0.854**
OLE_SB4	0.397	0.583	0.513	0.450	0.237	0.521	0.512	0.613	**0.890**

Source: from authors.

4.3 Assessing the Structural Equation Model

According to Joe F. Hair et al. (2011), the bootstrapping algorithm shall be used to assess the path coefficients' significance. The bootstrap subsamples parameter was configured as 10,000, a significance level of 0.05 (t value 1.96), two-tailed The path coefficients are the estimates that result from the SEM model and they refer to the hypothesized relationship among constructs. Table 7 captures the result of the structural model analysis for Model_1.

Table 7 –Model_1 – Structural Model Analysis

	Hypothesis	VIF	Effect Size (f2)	Path Coeff.	Standard Error	t-Value	P values	R^2	R^2 Adjusted
OLE -> IWB	H1(+)	2.722	0.002	0.057	0.177	0.322	0.747		
ACAP x OLE -> IWB	H2(+)	1.162	0.000	0.007	0.087	0.08	0.936	0.270	0.245
ACAP -> IWB	H3(+)	2.545	0.123	0.477	0.169	2.826	0.005		

Source: from authors.

For measuring collinearity, VIF (Variance Inflation Factor) was used and is the indicator of the effect that the other independent variables have on the standard error of a regression coefficient. Large VIF values also indicate a high degree of collinearity or multicollinearity among the independent variables (Joseph F. Hair, Hult, et al., 2014). When VIF exceeds 5 we may have variables that are highly correlated and may be redundant. The green values in Table 7 suggested that multicollinearity is not present on the sample used.

The effect size indicator f2 is used to assess the contribution, the substantive impact, of individual constructs to the endogenous constructs (J. Cohen et al., 2003). It tells how meaningful the relationship between variables or the difference between groups is. The larger the effect size is, the greater the practical significance of the research findings. According to Cohen et al., (2003), the guidelines for assessing f2 are: 0.02 (small), 0.15 (medium), and 0.35 (large). Thus a medium effect size was found in the relationship between ACAP and IWB.

The coefficient of determination (R2) reflects the model predictive capacity (accuracy) and is calculated as the correlation between actual values of a construct versus the predicted value calculated by the model. R2 varies from 0 to 1, the higher the value, the higher the predictive accuracy. As a rule of thumb (Joseph F. Hair, Hult, et al., 2014), we may consider R2 values of 0.75 (substantial), 0.50 (moderate), or 0.25 (weak). Because of the effect of adding more correlated constructs in a model into R2, there may be a bias towards models with a greater number of exogenous constructs. Thus, relying exclusively on R2 is not a good approach. To address that we can rely on the adjusted R2 value (R2adj), where the number of exogenous constructs and the sample size relativize the value of the original R2 Coefficient of Determination (R2 Value). Model_1 shows a weak predictive capacity (R2adj of 0,27).

Path coefficients refer to the hypothesized relationship among constructs, values vary from -1 to 1, the closer to the absolute value of 1, the stronger the relationship is. Nevertheless, the path coefficient should be understood regarding its significance. The significance of a path coefficient is measured by the indicator “t” calculated as the Path Coefficient divided by standard error calculated by the bootstrapping routine. For a significance of 5%, the “t” value should be greater than or equal to 1.96.

Therefore, the path coefficients where the p-value is less than 0.05 are considered significant implying that the H0 (null hypothesis) is rejected and only H3(+) is confirmed with path coefficient 0.477 ($p = 0.005$), and effect size medium.

To assess the Common Method Bias (CMB) this study relied on the measured latent marker variable” (MLMV) approach (Chin et al., 2012). The MLMV approach can detect and correct CMB using the Partial Least Square algorithm. It works by adding unrelated measures (survey items) as part of the original survey, but that does not keep a nomological relationship with the particular study. Then, they are as a control for each dependent construct in the research model Chin et al., 2012). By comparing the path coefficient between the model with/without control we notice no change in the path coefficient shown in Table 8. Thus, no variance is attributable to the measurement method.

Table 8 – Comparison for path coefficient (w/out) CMB

	Model_1 (Without CMB Control)	Model_1 (With CMB Control)
OLE -> IWB	0.057	0.057
ACAP x OLE ->	0.007	0.007
ACAP -> IWB	0.477	0.477

5 CONCLUSION

The objective of the present study was to understand the relationship between organizational learning from errors (OLE), absorptive capacity (ACAP), and innovative working behaviors (IWB) within teams. One out of the three hypotheses was confirmed suggesting that, in general terms, organizational learning from errors and absorptive capacity explains around 28% of the total variance in innovative work behaviors. Additionally, the H3 was confirmed and indicate that to promote innovative work behaviors the organization should improve the absorptive capacity, or in different terms, its ability to make sense and assimilate new knowledge.

The results showed that although OLE is similar to ACAP, they are still different constructs suggesting that innovative working behaviors are intricately related to the absorption of foreign knowledge and the capacity of mobilizing resources to put that new knowledge in motion. Feeling safe to report errors or comfortable trying new things may intuitively suggest that learning from errors could potentially be related to IWB, but our results do not corroborate that.

IWB happens in the presence of organizational and group context but depends prominently on individual traits where a proactive personality is associated with innovative behaviors (Al-Omari et al., 2019). Whereas, we may argue that OLE is a reflex in the individual of the group and organizational settings related to learning and experience of success and failure.

A limitation of this study is related to how data was collected, (i) as the sample is not probabilistic, it is not possible to generalize the results obtained; (ii) A person's response may not be representative of the organizational level construct such as ACAP.

For future studies, it is suggested to collect data from individuals of different types of organizations (public and private sector) as well as data in different moments, aggregating these responses to represent measures at the group level (company sector), thus increasing the reliability of results on such influences.

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