Learning Through Experimentation: Growth Hacking in Organisational Development Strategy

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Abstract: This article attempts to explore the role of continuous learning through experimentation, considered within the context of the concept of growth hacking. The turbulence of the environment and the pace of change in this field mean that modern organisations are faced with the need to react quickly, including making immediate decisions and introducing innovations. In light of this, the first part of this article presents the theoretical foundations of growth hacking and the closely related practice of experimentation. A review of the literature led to the formulation of the following research question: Does an organisation's general approach to experimentation influence its level of experimentation in technical terms? In the practical section, an attempt was made to verify the cause-and-effect relationship between these areas. To this end, the results of a survey conducted among 250 large and medium-sized IT companies in Poland in the second half of 2024 were utilised. The analysis was carried out in R, within which structural equation modelling (SEM) was developed. On this basis, it was found that a higher level of experimentation in general terms determines the level of technical experimentation. The final section of the article also highlights the limitations and directions for further research.

Keywords: Growth hacking, Experimentation, Learning, Structural equation modelling (SEM)

1. Introduction

The pace of change taking place in the organisation's immediate and wider environment has a significant impact on its competitive position. The turbulence of the environment and the need to maintain a specific market position force companies to take specific actions, which are usually immediate in nature. The operating conditions of modern enterprises dictate specific responses, within which experimentation is becoming particularly important.

Experimentation has gained significant popularity in the operations of modern enterprises. This is evidenced, among other things, by the increasing number of studies in this area, which confirm the benefits of its application, including improvements in a company's profitability in the initial phase of its operations and during its further development. The need for change arising from environmental dynamics means that, in this regard, a special role is attributed to the concept of growth hacking (GH), understood as the undertaking of experimental initiatives. Its aim is to define methods for scaling a business (Sanasi et al., 2023), that allow for the initiation of new development activities whilst maintaining the current level of resource commitment (Sanasi, 2025).

It is worth noting that the widespread adoption of growth hacking within a company involves accepting certain principles, namely:

- decision-making processes are based on large data sets,
- the solutions implemented are characterised by innovation,
- experiments often also involve digital innovation,
- continuous learning takes place on the basis of the experiments carried out,
- dynamic skills play a key role.

Organisations characterised by a strong focus on development embrace change (Korombel & Ławińska, 2025) . Consequently, they face the need to implement experiments and learning, which are considered the foundation of growth hacking (Giordino et al., 2025).

It should be assumed that growth hacking, viewed as a form of data-driven experimentation, contributes significantly to the process of continuous learning, which ultimately impacts the organisation's development and growth. Furthermore, it is emphasised that, through experimentation, this approach helps to bridge the gap between planning, formulating and implementing growth strategies. The following section of the article outlines the theoretical foundations of growth hacking from a learning perspective.

2. Literature Review

The term 'growth hacking' was first introduced in the literature by Sean Ellis, who defined it as 'process of rapid experimentation across the funnel to learn the most effective way to scale sustainable customer adoption' (Ellis & Brown, 2017). The growing interest in this concept in practice has led to it being viewed as a key factor in achieving rapid organisational growth. Although for a long time growth hacking was seen solely through the lens of start-up development, it has since come to be described as a 'data-driven approach to improving processes and activities through continuous experimentation'. It is assumed that growth hacking fosters product, process and organisational innovation (Schiavone et al., 2025).

GH is identified with taking rapid, experimental action (Rezazadeh et al., 2025). Creativity plays a key role in this area, as it determines the implementation of financially profitable initiatives – that is, those that generate profits without requiring the allocation of additional resources (Bargoni, Santoro, et al., 2024). It is worth noting that this approach has become particularly widespread among companies operating in the high-tech sector, which, due to their substantial digital resources, have significant potential for business scaling (Sanasi, 2025).

Organisations that promote the idea of experimentation as part of their activities must take into account the fact that not every experiment is successful. Nevertheless, even failure provides specific information that constitutes a valuable resource for the organisation (Migduła, 2026). Learning from mistakes is regarded as the foundation of a learning organisation, which improves through continuous learning processes and the practice of knowledge sharing. As Cristofaro et al. note, improving these processes is possible through regular meetings on the experiments being conducted. This approach ensures that activities remain aligned with business objectives, that the learning process is sustainable, and that the organisation develops progressively (Cristofaro et al., 2025).

An organisation's ability to learn enables it to adapt quickly to the current market situation. Furthermore, it involves deepening knowledge and transferring it within the company. It plays a significant role in growth hacking, which relies on rapid implementation and the ability to adapt to market changes. This is an essential prerequisite for gaining a competitive advantage (Foggetti et al., 2025).

As highlighted in the literature, an organisation's intellectual potential determines its development in the field of growth hacking, where learning processes are driven by experimentation. This, in turn, relies on large datasets, which form the foundation of knowledge management. Experimentation shapes learning processes and inspires organisations to innovate. Learning from mistakes and repeating actions aimed at optimising performance play a particular role in this context. The experience gained in this way is further reinforced by growth hacking, which ultimately intensifies learning processes and determines market outcomes (Schiavone et al., 2025).

In the context of the topic under discussion, it is worth noting that the concept of growth hacking involves transforming collected data into knowledge, which has a significant impact on learning processes (Bargoni, Santoro, et al., 2024a). Growth hacking is a way of embedding an approach to collecting and analysing large datasets within decision-making processes. It is argued that organisations should focus on acquiring and verifying data, and then transforming it into information and knowledge, as these activities significantly support learning processes and contribute to the development of innovation (Bargoni, Smrčka, et al., 2024; Troisi et al., 2020).

Santoro et al. suggest that growth hacking has not yet been sufficiently analysed in a management context, where it should be considered through the prism of innovation, growth strategy and entrepreneurship (Santoro et al., 2026). This raises the question: how do organisations understand and approach experimentation? It is worth noting that experimental methods such as growth hacking are often seen as the link between strategy development and its implementation (Sanasi, 2025).

As noted Bargoni et al. (Bargoni, Jabeen, et al., 2024; Bargoni, Smrčka, et al., 2024) growth hacking should be viewed as a data-driven decision-making process that enables the implementation of rapid, short-term experiments in the field of strategic management (Giordino et al., 2025). This integration of data analysis and the learning process enables decision-making that aligns with customers' expressed needs. In this context, growth hacking provides the conditions for an organisation to adapt quickly to a turbulent environment. It is worth emphasising here that growth hacking is also viewed through the prism of dynamic capabilities (Teece, 2010, 2018). The collection and analysis of big data plays a crucial role in this context, particularly in terms of fostering a data-driven mindset (Gerlich et al., 2025).

Growth hacking is a determinant of dynamic growth, achieved through the integration of continuous learning and ongoing experimentation. It enhances organisational potential, enables adaptation in a competitive environment, and boosts short-term performance metrics. It emphasises the importance of gathering information about users and the need to tailor the product to their expectations (Bargoni, Santoro, et al., 2024).

These measures have a significant impact on consumers' decision-making and their long-term loyalty (Amoozad Mahdiraji et al., 2025).

Joshi et al. following Bohsnack and Liesner (Bohsnack & Liesner, 2019) highlight the unconventional nature of growth hacking, particularly in terms of bridging the gap between the formulation and implementation of strategic objectives (Troisi et al., 2020). They point out that the development of dynamic capabilities to date, together with the widespread adoption of experiments based on data collection and analysis, has helped to enhance the organisation's capacity to implement modern technological solutions and business models (Joshi et al., 2025).

A common feature of the aforementioned approaches to the concept of growth hacking is the frequent integration of two processes: continuous learning and decision-making (based on large datasets) (Giordino et al., 2025). The literature on the subject emphasises that this approach allows strategic objectives to be adapted to the conditions of a constantly changing environment. The term 'growth hacking' is based on rapid experimentation, closely linked to the dynamic capabilities possessed by organisations, which are considered essential in the context of a company's development in the broadest sense. It is worth noting that these capabilities do not serve solely to streamline the decision-making process, but are aimed at introducing innovations and prototypes that meet reported market demand (Scuotto et al., 2025).

In light of the above, it can be concluded that the introduction of rapid, short-term experiments significantly contributes to continuous learning, which ultimately determines an organisation's potential. The uncertainty of the environment and the dynamics of the changes taking place within it mean that a key role is attributed to innovative solutions, which, in practice, facilitate the planning and implementation of strategic objectives.

In this regard, the following research question was posed: Does an organisation's general approach to experimentation influence its level of experimentation in technical terms?

3. Methodology and Results

The empirical section of the article attempts to verify the cause-and-effect relationships between selected variables. To this end, structural equation modelling (SEM) was applied, which enables the testing of relationships between observable and latent variables and allows for the estimation of unobservable variables (Sagan, 2003; Zasuwa, 2011).

The variables used to develop the SEM model were obtained from a survey conducted in the second half of 2024 among 250 companies in the IT sector. The questions in the survey questionnaire were rated on a Likert scale (1–5). They concerned the area of experimentation and were divided into two groups for the purposes of model construction. The first group of questions focused on experimentation in the technical dimension, highlighting the use of: social media, Artificial Intelligence, Design Thinking, Lean Startup, Agile, Agile Scrum and Kanban. The second group emphasised the respondents' general approach to experimentation. In this regard, aspects related to, amongst others, the direct involvement of employees and stakeholders in business processes, the development of multidisciplinary teams, the creation of product and process innovations, and continuous learning processes in the face of failure were taken into account. These variables were labelled respectively: EXPTech (E2:E8) and EXP (E9:E14). They are included in Table 1. The analysis was conducted in R. The results obtained in this regard are presented below.

Table 1: Variables used in the study

Experimentation in the technical dimension (EXPTech)	
E2	We experiment by using social media
E3	We experiment by using artificial intelligence (AI)
E4	We experiment by promoting a modern approach to management, which is: Design Thinking (careful understanding of customer needs, based, among other things, on empathy)
E5	We experiment by promoting a modern management approach, such as: Lean Startup (experimenting with the initial, simplest version of the product, which is then tested on customers)
E6	We experiment by promoting a modern approach to management, which is: Agile (dividing the project into stages, i.e. according to the priorities of individual tasks, which facilitates the introduction of modifications)

Experimentation in the technical dimension (EXPTech)	
E7	We experiment by promoting a modern management approach, which is: Agile Scrum (based on daily meetings during which progress and difficulties related to the implementation of a given task are discussed – these meetings are attended by the client and the Scrum Master)
E8	We experiment by promoting a modern approach to management, which is: Kanban (visualisation of workflow using a Kanban board)
General approach to experimentation (EXP)	
E9	We experiment by engaging employees to generate ideas
E10	We experiment by engaging stakeholders to understand their needs
E11	We experiment by developing multidisciplinary teams
E12	We experiment by creating product/service innovations
E13	We experiment by creating process innovations
E14	When the experiments we implement end in failure, we rely on the process of continuous learning and introduce further new experiments

Firstly, attention was paid to the model's fit to the data (Table 2). It is worth noting that initially 15 variables were used to build the model; however, in order to obtain the best possible fit indices, modifications were made, and ultimately two of them were rejected.

Table 2: Fit indicators

Name	Value
Comparative Fit Index (CFI)	0.943
Tucker-Lewis Index (TLI)	0.931
Root Mean Square Error of Approximation (RMSEA)	0.055
Standardized Root Mean Square Residual (SRMR)	0.048

The information in Table 2 indicates that the model fits the data very well. The CFI stood at 0.943, whilst the TLI was 0.931; in both cases, it was >0.9. The RMSEA value was 0.055, suggesting it lies on the borderline between satisfactory and good results. The SRMR index of 0.048, in turn, suggests an ideal fit. The fit assessment was conducted solely on the basis of the above indices. The table does not include the chi-square test, which was significant ($\chi^2(64) = 111.98$; $p < 0.01$). It should be assumed that this result is due to the large sample size (n=250), which in practice leads to high statistical sensitivity and results in the unjustified rejection of models with a good fit.

In the next step, the construct's reliability and validity were assessed. The results in this regard are presented in Table 3.

Table 3: Reliability and validity indicators

	Internal Consistency Reliability				Composite Reliability	AVE
	alpha	omega	omega2	omega3		
EXPTech	0.7619731	0.7632550	0.7632550	0.7618204	0.762	0.319
EXP	0.7904802	0.7950938	0.7950938	0.7982980	0.798	0.397

The reliability and validity of the constructs were assessed using the following measures: Internal Consistency Reliability (α, ω), Composite Reliability (CR) and Average Variance Extracted (AVE). The alpha and omega coefficients indicate acceptable reliability for both constructs (α = 0.76–0.79; ω=0.76–0.79). The Composite Reliability values were very similar, indicating good reliability for the constructs. Convergent validity, assessed using AVE, was on the borderline of acceptability for the general approach to experimentation, i.e. at 0.397, whilst experimentation in technical terms fell below the recommended threshold (0.319). Nevertheless, as the literature on the subject demonstrates (J. F. Hair et al., 2025; J. F. J. Hair et al., 2010) high reliability indices (α, ω, CR) compensate for the lower AVE values, and the study was therefore considered to meet the validity criteria. It was assumed that the quality of the measurement was in line with accepted standards; consequently, the relationships between the latent variables were presented in the subsequent stage (Table 4).

Table 4: Standardized factor loadings (Std.all) for the measurement model

Construct	Item	Completely Standardized Estimates (Std.all.)
EXPTech	E2	0.577
	E3	0.465
	E4	0.603
	E5	0.516
	E6	0.722
	E7	0.477
	E8	0.573
EXP	E9	0.697
	E10	0.557
	E11	0.595
	E12	0.710
	E13	0.674
	E14	0.509

Table 4 presents the completely standardised estimates for each observable variable. Experimentation in the technical dimension was verified by variables E2–E8, whilst the general approach to experimentation was verified by variables E9–E14. The highest value of the indicator in the first construct was recorded for variable E6 (0.722), indicating a strong relationship with EXPTech. The lowest loading values, in turn, were for variables E3 (0.465) and E7 (0.477); however, taking the fit assessment into account, these values were deemed acceptable (modifying the model and removing the variables did not improve the fit parameters). The remaining estimate values fluctuated above 0.5, suggesting that the construct was defined correctly.

The results obtained in the next area, i.e. the general approach to experimentation, show that all variables are >0.5 and therefore reflect the latent construct well or very well. The p-value in each case is <0.001, and therefore these variables should be considered statistically significant. It was assumed that the constructs were defined correctly; consequently, the parameters of the SEM structural model are presented in the next section (Table 5).

Table 5: SEM model parameters

Path	Std.all	p
EXP→EXPTech	0.796	<0.001

The parameters presented in Table 5 enable an assessment of the strength of the relationship between the latent constructs. The value of the β coefficient in this case was 0.8, which indicates a strong, statistically significant relationship ($p<0.001$). The results obtained suggest that the popularity of the general approach to experimentation explains experimentation in a technical sense. An increase in interest in experimentation in business activities leads to a rise in practical activities focused on technical experimentation.

A graphical summary of this interpretation is presented in Figure 1.

Figure 1 presents a graphical representation of the SEM model, highlighting the strong positive relationship: $\beta = 0.796$ ($p<0.001$) between the latent constructs, namely general experimentation and technical experimentation (the constructs are represented as circles). The factor loadings of the individual observed variables (represented as squares) ranged from 0.465 to 0.722 for the EXPTech construct and from 0.509 to 0.710 for EXP. Although the loadings for two variables fell below the recommended threshold of 0.5, they were deemed acceptable, as their removal did not improve the model's fit to the variables.

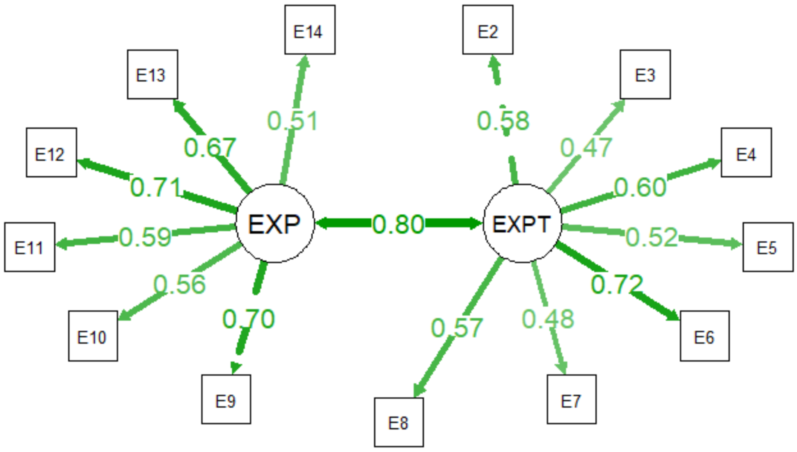

Figure 1: Graphical presentation of the SEM model

4. Conclusions

The results of the analysis indicate that both of the examined areas (latent constructs) were adequately explained by the observable variables. The general approach to experimentation was defined as:

- actively engaging employees and stakeholders in the business process,
- developing multidisciplinary teams,
- creating innovation,
- relying on a process of continuous learning when experiments fail.

Experimentation in technical terms is, in turn, presented as the application of diverse business practices, including: social media, AI, Design Thinking, Lean Startup, Agile, Agile Scrum and Kanban.

Experimentation plays a key role in the modern approach to doing business, particularly in light of the changes taking place in a turbulent environment. These activities are regarded as unconventional, and their primary aim is to improve efficiency, which ultimately enables a company to stand out from the competition. As noted above, experimentation takes place at various levels of an organisation's operations and may concern customers, stakeholders, innovation, as well as the specific nature of the business.

High factor loadings for the variables "employee engagement in the business process" and "introducing product and process innovations" constitute a strong and accurate indicator of the latent construct of "general approach to experimentation." It can be assumed that these aspects most closely reflect the perception of experimentation among the surveyed companies. In turn, the construct of "technical experimentation" was best reflected by the promotion of Design Thinking (focused on understanding customer needs, based, among other things, on empathy) and Agile (a solution that divides the project into stages, i.e., according to individual tasks). The weakest factor loadings (<0.5, but considered significant) were observed for AI and Agile Scrum. This result suggests that for many IT companies, these are not experimental solutions aimed at seeking unconventional methods of progress, but merely tools to improve organizational functioning. They can be perceived as a standard of digital development (artificial intelligence), the implementation of which seems essential to maintaining current market position, or as common operational practices (Agile Scrum) aimed at improving performance indicators. Differences in approaches to experimentation may, in this case, stem from the varying levels of maturity of the companies studied in this regard. This is evidenced, among other things, by the fact that two variables were eliminated from the model at the initial stage of its development, i.e., variable matching. It can be assumed that companies with high maturity consider the use of Big Data commonplace. A similar situation occurred with the variable: abandoning subsequent experiments if previous ones were unsuccessful.

Experimentation drives learning, and therefore all companies that experiment actively participate in the process of continuous learning. This, in turn, impacts the effectiveness of strategy planning, formulation, and implementation.

The dissemination of experimental activities is characteristic of learning organisations focused on permanent development. Taking initiatives in a general sense creates the conditions for implementing more specific experiments, and therefore, a higher level of experimentation in general fosters experimentation in the technical dimension. This confirms the previously posed research question.

5. Limitations and Directions for Further Research

The limitations of this study include its exclusive focus on a single industry, IT. Including an additional sector in the analysis could provide a broader perspective on companies' experimentation approaches. Furthermore, the results obtained in this area are dictated by the turbulent environment. The dynamic development of digital technologies, particularly the significant emphasis on AI, largely determines pro-innovation behaviour. Limitations may also result from varying levels of experimentation culture within companies, both in general and technical aspects.

The studied constructs were narrowed to a few variables, so it seems reasonable to expand them later to include additional aspects of experimentation. It is assumed that subsequent research will verify the impact of experimentation on specific areas of an organisation's strategic management.

Ethics Declaration*:* Consent was not required to conduct this research.

AI Declaration*:* AI tools such as ChatGPT were used during the development of this article. This tool was used for supporting purposes only.

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