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Building expertise: How do firms improve product quality based on Breadth/Depth of experience and proper timing during incremental and radical changes?

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Abstract

This study contributes to the NPD oriented literature that focuses on investigating the role of firms' technological experience, timing of adoption of a new technology, and technological changes in alteration of product quality. We conceptualize technological experience through two dimensions (Depth and Breadth of experience) and investigate how each dimension affects the quality product when incremental and radical changes occur. In addition, we analyze how different dimensions of experience interact with the timing of adoption of new technologies. The main results of the empirical analysis performed on the example of video game industry show that (1) firms benefit directly from Depth of experience only when there are incremental technological changes whereas Breadth of experience does not cause any direct significant impact on firms' performance when there are incremental technological changes; (2) prolongation of time for product development has a positive effect on the product quality for firms with extensive Breadth of experience.

Jelcodes:O32,O31

INTRODUCTION

Certain industries are confronted with exogenous innovations or emergence of new technologies which need to be used as an input for NPD. The availability of new technologies forces firms to update their routines, and, if needed, install new procedures. While facing these technological changes and establishing routines, firms gain experience that becomes one of the crucial intangible resources.

Firms benefit from experience differently depending on radicalness of technological changes (Eisenhardt and Martin, 2000; Pavlou and El Sawy, 2011). Researchers recognize two types of technological changes: radical and incremental ones (Dewar and Dutton, 1986). Facing incremental changes, firms learn how to utilize the existing technology more effectively or gain knowledge about new sub-technologies which allow increasing performance of core technologies (Teece et al., 1997). When firms adopt radical technologies to their NPD processes, firms gain knowledge about new technologies, create new, never existing before, values or master new ways of production. Acquisition of new knowledge enriches firms experience but can cause obsolescence of old knowledge. Hence, by facing radical and incremental technological changes firms accumulate two different dimensions of experience – the one that reflects the extent of the exploitation of the same technology, and the other one that reflects the extent of the exploitation of different generations of technologies. These experiences lead to the deepening of the existing knowledge in the former case, and its broadening in the latter.

In our study we aim to investigate the effect of firms' experience with respect to both radical and incremental technological changes on the firms' ability to produce high-quality products. In this sense, our study is the first to address both dimensions of experience in relation to product quality. We also do it from both theoretical and empirical perspectives. In particular, the study reconciles literature on new product development (NPD) with the studies incorporating organizational learning theory, the knowledge-based or dynamic capabilities views. In the knowledge-based view and NPD literature scholars put emphasis on the effect of depth and scope of knowledge (Caner and Tyler, 2014; Katila and Ahuja, 2002) while in organizational learning and the dynamic capabilities literature scholars analyze the ability of firms to cope with radically or incrementally changing environment (Eisenhardt and Martin, 2000; Pavlou and El Sawy, 2011) and learn from the experience acquired within this environment (Argote, 1999; Crossan et al., 1999). Although these two streams in the literature address similar questions, there is a missing link between them. Knowledge depth and knowledge scope reflect the dual nature of firm's knowledge portfolio but they do not account for the dynamics of knowledge creation or knowledge acquisition. Organizational learning and the dynamic capabilities view, in turn, suggests that learning takes place via encountering incremental and radical changes but they neglect the role which knowledge depth and knowledge scope play in determining product quality. We argue that by focusing on experience, we should be able to account for the dynamism of knowledge accumulation and at the same time capture heterogeneous effects of the two dimensions of knowledge on firms' performance. Thus, we believe that studying the role of experience rather than knowledge will serve as the main link between the two streams of literature and bring new theoretical implications.

Experience explicitly reflects the extent to which a firm encounters incremental and radical changes. Encounters with incremental change can easily enhance the firm's depth of knowledge as it develops new products using the same technologies. Encounters with radical change provide firms the opportunity to broaden knowledge by developing new products based on radically different technologies. The analysis of these two dimensions of experience rather than firm's routines, capabilities or diversity of knowledge portfolio provides different insights on the effect of technological change on the NPD process and change in product quality. In addition, it allows estimating whether firms equally benefit from both dimensions of experience when radical and incremental technological changes occur.

Experience is one of the main intangible assets of a firm that influence product quality (Argote and Miron-Spektor, 2011). However, it does not bring much without appropriate timing of the introduction of a new technology in the production process. When a new technology emerges, there is a dilemma for firms whether to adopt it immediately and develop a new product based on this technology, or use the prior technology, learn how to master a new one, experiment and wait until the new technology is well established and all negative effects related to its prompt adoption, are taken by other firms. Timing is a factor which may be beneficial or harmful for firms under different circumstances. An extensive number of works has investigated under which circumstances firms benefit from being the first, the second, or a later adopter of a new technology (Lieberman and Montgomery, 1998; Suarez and Lanzolla, 2007). However, the role of timing in the new product release is understudied in the NPD literature (Fisch and Ross, 2014; Peres et al., 2010) and the combined effect of timing with two-dimensional experience (depth and breadth) has been widely neglected. In our study we aim to fill in this research gap by analyzing the moderated effect of timing on experience and product quality from the empirical point of view, and its theoretical implications for the literature on NPD, the knowledge-based view, organizational learning theory, the dynamic capabilities view, and the first-mover advantage. Up to our knowledge, there are no empirical studies that investigate how previous NPD experiences with different generation of technology and technological platforms contribute to future success. We hope that our study makes a valuable contribution to current academic literature.

CONCEPTUAL BACKGROUND

In recent innovation studies, we observe a trend of merging different theoretical approaches in an attempt to explain the role of certain phenomenon. Our study lies on the edge of the knowledge-based view (Felin and Hesterly, 2007; Grant, 1996); organizational learning theory (Argote and Miron-Spektor, 2011; Crossan et al., 1999; Fiol and Marjorie, 1985); the dynamic capabilities view (Eisenhardt and Martin, 2000; Teece et al., 1997); and the concept of first-mover advantage (Lieberman and Montgomery, 1988). Albeit from different perspectives, these theoretical approaches discuss the same concepts of firms' experience and knowledge, the impact of changing technological environment and timing of adoption of new technologies on firms' performance. We do not aim to encrust all these elements in one specific theoretical trajectory. Instead, we aim to enrich our knowledge on the interplay of these three elements by analyzing empirically which role they play in predetermining the product quality.

According to Anderson and Tushman (1990) and Foster (1986), technological standards cyclically substitute each other. When a dominant design is set, firms exploit the dominant technology and implement incremental innovation processes (Anderson and Tushman, 1990). The development of products based on the same technology enriches firms experience and deepens their knowledge (Teece et al., 1997). At the stage when one dominant technology is substituted with another one, firms are forced to explore this new technology (Agarwal and Helfat, 2009; Klarner and Raisch, 2013; Lavie, 2006). If firms successfully master the new technology they shift again to the stage of exploitation of the dominant technology and incremental innovations.

Cyclical recurrence of new technologies and repetitive exploration of these new technologies by firms broaden their experience. Experience is one of the main elements of competitive advantages of any firm (Faraj and Sproull, 2000; Itami and Roehl, 1987; Zahra and George, 2002). Organizational learning and NPD literature suggest that the greater the experience the firm has the quicker and better it understands the new technology and its advantages, and the more effective its exploitive and explorative learning is (Argote et al., 2003; Caner and Tyler, 2014; Li et al., 2013; March, 1991). Departing from this, Katila and Ahuja (2002) propose two dimensions which reflect (1) the level of reuse of existing knowledge, and (2) the scope of new knowledge exploration. In our study, we follow this logic for the measurement of firms' experience. We assume that extensive development of products based on the same technology enriches firms' depth of experience and knowledge, while encountering and surviving numerous generations of new technologies widens firms' breadth of experience and knowledge. We distinguish these two types of experience since firms act differently when mastering the same technology or exploring a new one.

We draw upon theories of organizational learning and the knowledge-based view to understand how experience links to knowledge and performance. These theories show how firms gradually improve their activities via experimenting and improvising with new technologies (e.g. Bingham and Davis, 2012); how firms transfer knowledge from other domains and recombine them with existing knowledge (Nesta and Saviotti, 2006; Yayavaram and Chen, 2015); and how firms learn from the experience of other firms (Ingram, 2002). These studies strictly distinguish firms as experienced (incumbents) or inexperienced (newcomers), thereby neglecting firm's variation in the type and degree of experience. We assume that the depth and breadth of experience varies not only between incumbents and newcomers but also among incumbents. We argue that assessment of dissimilarities in extent of depth and breadth of experience among firms is a better proxy for measurement of firms' maturity rather than definition of maturity at two levels (incumbents vs. newcomers).

Technologically unstable environment requires firms to develop dynamic capabilities for surviving radical technological changes, while substantive capabilities are suited for the optimization of production processes when firms encounter incremental technological changes (Helfat and Peteraf, 2003; Winter, 2003; Zahra et al., 2006). This two-dimensional characteristic of technological environment provides evidence about two different sources for knowledge accumulation and implies that firms benefit from the experience differently.

Firms that have acquired a lot of depth of experience by having introduced many new products with the same technology may exploit acquired knowledge well in situations where the technological change in the market is rather predictable and incremental. Firms that have acquired a lot of breadth of experience by having introduced many new products using radically different technologies may exploit acquired knowledge well in situations where the technological change in the market is rather unpredictable or radical. However, not only experience, substantive and dynamic capabilities define firms' NPD performance but also timing of adoption and exploitation of new technologies plays an important role in firms' NPD performance (Lieberman and Montgomery, 1988). The argument behind is that experienced and inexperienced firms may benefit differently from the fast adoption of new technologies (Benner, 2007; Fisch and Ross, 2014; Rasmusen and Yoon, 2012). Given the same timing, experienced firms may better understand how to apply new technologies and experiment with them simultaneously with organizing or adjusting the development process whereas inexperienced firms may apply a new technology without proper understanding of how to deploy all new features of it which might lead to a bad NPD performance. From this perspective, it would make sense to consider the role of experience not through its direct effect on product quality but through the prism of its interaction with timing of adoption of new technologies. To the best of our knowledge, this issue has not been explicitly addressed in prior studies.

HYPOTHESES

This study builds on the following assumptions: (1) firms' expertise increases with a greater number of product developments, (2) firms develop products of a higher quality when they gain more expertise, (3) firms' breadth and depth of experience are distinct forms of experience that differently impact product quality, depending on the radicalness of technological changes being faced by firms; (4) experienced and inexperienced firms may benefit from late product releases in a different way.

Depth of experience

A stable and unchanging environment is a precondition for enrichment of depth (intensity) of experience (Polanyi, 1983). Such environment allows firms to gradually improve their routines via continuous exploitation of core technologies in the absence of pressure of technological shifts (Eisenhardt and Martin, 2000). Firms have a sufficient amount of time to identify all weaknesses of the process of production optimization and eliminate them via a repetitive use of the same technology (Teece et al., 1997). With an increase in this type of experience, firms obtain better chances to avoid mistakes that were made in the past; to establish routines that are necessary for substantive capabilities; accelerate the product development process; to improve existing products to the level of their maximum performance within existing technological limits; to optimize production costs; to improve products' design; and to explore consumer preferences. An optimized in this way production process and a minimized number of products' defects guarantee positive changes in product quality.

Accumulation of depth of experience is also accompanied by jeopardies. First of all, the process of gaining experience or accumulating knowledge by itself may cause problems. While exploiting a certain technology, firms may become inert to further technological exploration (Hannan and Freeman, 1984). They might lock themselves within one technological trajectory, trying to gain maximum benefits from a core technology and unwilling to explore new technologies (Hannan and Freeman, 1984; Levinthal and March, 1993). Such a state of affairs leads to negative outcomes when technological environment loses its stability and becomes turbulent. As mentioned above, technological changes can be considered as radical and incremental ones (Garcia and Calantone, 2002; Utterback, 1996). All technological shifts within a certain technological trajectory which are not followed by the emergence of brand new products but rather associated with improvements of existing products are deemed to be incremental (Garcia and Calantone, 2002; Song and Montoya-Weiss, 1998). Contrarily, technological shifts which are convoyed with the emergence of new to the world products, that encompass technologies which have never been used before in this technological trajectory, are deemed to be radical (Colarelli O'Connor, 1998; Garcia and Calantone, 2002).

In this context, firms which apply or introduce new technologies may disrupt inert and inflexible firms which are locked in one technological trajectory (Danneels, 2004). In addition, by being attached to one technology and lacking knowledge about the new technology, firms may attempt to apply already mastered and established techniques and routines for mastering of a new technology (Betsch et al., 2004). The established routines and knowledge, however, may be nontransferable to the new setting imposed by the emergence of a radically new technology, and firms will need to unlearn established practice and adopt new ones. In turn, it might negatively impact NPD process and the quality of a new product. Based on these facts, we hypothesize the following:

Hypothesis 1. Depth of experience positively affects product quality when there are incremental changes, but negatively when there are radical changes in the industry.

Breadth of experience

Gradual and systemized adoption of new technologies by firms reflects their ability to cope with uncertainties and threats which are imposed by these new technologies (Klarner and Raisch, 2013; Teece, 2014). Knowledge accumulated via encountering radical technological changes foster firms' capabilities which allow surviving radical changes in the future. Only by surviving a radical technological change firms may learn how to build their strategy in a way that allows decreasing the costs of transition from the old technology to a new one (Klarner and Raisch, 2013; Teece, et al., 1997). This knowledge, in turn, might allow them to perform better compared to less experienced competitors when radical technological changes occur.

However, although breadth of experience is naturally beneficial during uncertainties caused by radical technological changes, it may become useless or even harmful when changes are incremental. Coping with incremental changes requires routinized and predictable activities while coping with radical changes may force firms to act reactively and experimentally. Based on these facts, we hypothesize that:

Hypothesis 2. Breadth of experience positively affects product quality when there are radical changes, but negatively when there are incremental changes in the industry.

Moderating Effect of Timing Strategy

Depth and breadth of experience are essential factors for firms' NPD performance but technological advantage is also achieved with appropriate timing of the adoption of new technologies and introduction of new products (Fisch and Ross, 2014; Lieberman and Montgomery, 1988; Suarez and Lanzolla, 2007). Quick adoption of a new technology and quick release of a new product may cause a disruption of the entire industry (Christensen, 1997). Firms that introduce such a technology may establish and maintain technological advantage for a long period of time.

However, prompt adoption of a new technology does not always bring benefits (Cho et al., 1998; Kim and Lee, 2008; Lieberman and Montgomery, 1988; Rodriguez-Pinto et al., 2011; Sood and Tellis, 2011). One of the main challenges for firms when a new technology emerges is cultivation of the best product design which will facilitate all features of a new technology and enable the product's performance to the maximum level. Development of the best product design is associated with the competition of various designs that eventually leads to the establishment of one widely accepted product design (Anderson and Tushman, 1990;

Henderson and Clark, 1990; Lambe and Spekman, 1997; Peng and Liang, 2016; Srinivasan et al., 2006; Tushman and Anderson, 1986). Competition of designs takes time and firms which have quickly adopted a new technology will not necessarily win in this competition of product designs. Failure of fast adopters of a new technology to release a product that will be widely accepted by a market provides a 'broad avenue' for adoption of a new technology and release of a new product by other competitors (Lieberman and Montgomery, 1998). Firms which do not release products immediately with the new technology have more time to experiment with it, develop a more elaborated design and omit mistakes which have been made by fast adopters (Suarez and Lanzolla, 2007). This also helps to save some resources for technological exploration and market intelligence. Both strategies significantly rely on timing: whereas fast adopters consider how to develop new products of a higher quality and release them faster than competitors, anticipants or followers consider how to adopt all novelties, and avoid mistakes.

The effect of timing of adoption of new technologies may alter the transition from firms' experience to product quality. When firms encounter a radical technological change, the positive effect of breadth of experience can deteriorate if they release products based on a new technology too fast. Therefore, experienced firms will not release a new product until it satisfies, already existing, needs and it brings some new additional values. In other words, a waiting strategy (extensive timing) might intensify the effect of breadth of experience.

On the contrary, with the increase of depth of experience and sustainability of an incrementally changing technological environment, a long waiting may harm product quality Argote (1999). On the one hand, extensive depth of experience leads to optimization of production processes and improvement of firms' routines and substantive capabilities. On the other hand, competitors, who simultaneously enrich their depth of experience at a faster rate, may also improve their production process faster and establish a higher 'bound' for product quality. In addition, the knowledge gained from experience devaluates over time (Argote, 1999) and long waiting may be especially detrimental when knowledge is acquired in incrementally changing environment. Hence, we hypothesize that:

Hypothesis 3. The time-to-react weakens the effect of depth of experience on product quality: the more time it takes firms to develop new products using a new technology, the less they benefit from depth of experience.

Hypothesis 4. The time-to-react strengthens the effect of breadth of experience on product quality: the more time it takes firms to develop new products using a new technology, the more they benefit from breadth of experience.

METHODS

Setting

We use the personal computer (PC) video game industry as an empirical setting for our study. The video game industry is a rapidly developing one with a large number of companies operating on the market. In 2013, globally there were 1458 PC video game developers who produced 2243 PC video games of different genres.[1] Worldwide sales in the entire industry were estimated at the level of $93 billion in 2013 (ESA, 2015). It is a knowledge-intensive industry where firms compete for better quality and design of software products (video games) based on different generations of hardware technologies.

All companies within the PC video game industry operate on the DirectX technological platform. DirectX application facilitates interaction between hardware components and video games in Microsoft Windows operational system. It serves as multiple application programming interfaces which standardize programming of interactive software based on different hardware platforms. Technological changes in PC hardware components

[1] According to the data published in GameRankings

(microprocessors, video cards, random access memory and others) accumulate and reach a certain limit over time. Based on technological changes in PC hardware components, Microsoft Corporation, on a continuous but irregular basis, introduces a new generation of DirectX application that incorporates all radical and incremental changes within the hardware components. The new generation of DirectX application replaces its predecessor and video game developers, gradually, start shifting their products to the new version of DirectX. Products designed for the prior version of DirectX slowly become obsolete (compared to the products oriented on the new version of DirectX) and at a certain point in time disappear from the market. Between 1995 and 2015, 10 main versions of DirectX (radical shifts) and 16 additional iterations (incremental shifts) were released. Table 1 summarizes the main innovations of the major versions of DirectX.

INSERT TABLE 1 ABOUT HERE

The shifts from prior to novel versions of DirectX force video game developers to learn new techniques of programming. Acquisition of new programming techniques increases variation (breadth) and intensity (depth) of firms' experience. Companies which have already faced a disruption of a several generations of DirectX accumulate more knowledge and skills which might be crucial for the development of products when a new version of DirectX emerges. All these features make the PC video game industry an appropriate setting for measuring the effects of depth and breadth of experience on firms' performance.

Sample and Data

This study relies on data from different independent sources (VGchartz; GameRankings; MobyGames; GiantBomb; Statista) covering the period between 1995 and

2014. [2] First, we derived information about the version of DirectX for each video game from the MobyGames dataset. Second, we acquired information about video game scores and names of video game developers for each video game from the GameRanking dataset. Third, we acquired information about the date of release; the name of video game publisher; a genre for each video game from the VGchartz dataset. Forth, we acquired information about the geographical location of each video game developer from the GiantBomb dataset. Other (secondary) web-resources were used to impute missing data (LinkedIn, Wikipedia, and IGN). After the merge of all these datasets, the number of observations reached 1082. Detailed description of the data (means, standard deviations and the correlation matrix) is in Table 2.

INSERT TABLE 2 ABOUT HERE

Measures

Dependent variable: Product quality. Availability of product quality indicators is one of the distinctive features of video game industry that allows seeing how successfully firms utilise all available technologies and accumulated experience. These indicators are based on critical reviews of video game experts which are combined in overall aggregated scores and posted on the Metacritic and GameRankings web-resources. The aggregated score ranges from 0 (the lowest) to 100 (the highest). We preferred expert-based scores to user-based scores since the expert-based scores are less affected by relative success of products. In addition, users tend to assign to a product scores which are close to the already assigned average score of this product. Thus, following previous research (e.g., Elliott and Simmons, 2008; Hennig-Thurau et al., 2006), we use expert scores as proxies for product quality in our study.

[2] VGchartz (www.vgchartz.com); GameRankings (www.gamerankings.com); MobyGames (www.mobygames.com); GiantBomb (www.giantbomb.com); Statista (www.statista.com).

Independent variables:

Depth of experience reflects the extent to which the firm has dealt with one certain platform technology (version of DirectX) and is measured as a number of products (video games) developed using the same platform technology. When the firm applies a new technology and releases the first new product, depth of experience is equal to zero since the firm has not released products based on this technology in the past. We also operationalized the variable in an alternative way. In the alternative specification, it reflects the number of products developed on the current technology or the number of products developed on the prior technology if there is a radical technological change and the new technology is applied for the first time to develop a new product. Hence, at the moment of the first product's release, the variable reflects the impact of past knowledge.

Breadth of experience captures firm's experience with different generations of technologies (versions of DirectX). It is measured as a number of platforms' technologies that have been used by a firm for the development of its previous products before launching a new one. Thus, for both depth and breadth of experience variables we applied Argote's and Miron-Spektor (2011) logic of operationalization. According to them, the best way to operationalize experience is to count the number of products and services that were released or performed in the past.

Time-to-react (moderator) reflects how fast firms apply a new technology (version of DirectX) after its invention. It is operationalized as the number of months that have elapsed between the official release date of a given version of technology and the date of release of a product based on this technology.

Incremental change and Radical change. These two conditions reflect the type of technological change that firms encounter. If there is a shift between iterations of the same version of DirectX, or there are no any shifts within a given version of DirectX (e.g., when

DirectX version 8.0a supersedes version 8.1) [Table 1], then we consider it as an incremental change. If there is a shift between different versions of DirectX (e.g., from DirectX version 9 to 10), then we consider this as a radical change. Following this logic, we split the sample in two subsamples. In the first subsample we included only those products which are based on technologies that have already been used by firms (incremental shifts). The second subsample consists only of the products based on new technologies at the moment of their first-time use by firms (radical shifts).

Control variables:

We also use a set of control variables to provide a stronger test of our hypotheses. These are product, firm and market specific variables which can be both time-variant and time-invariant.

Sequel of the video game. This control variable reflects whether a new video game is the first release or a continuation (sequel) of previous video games. There is a difference in the expectations of experts for the video games released for the first time and their sequels. Sequels are constantly compared by experts with their predecessors while first released video games do not have such a problem. To avoid a possible bias caused by experts that differently evaluate video games, we decided to control for it. The sequel variable is operationalized as a dummy variable, where ‘1’ stands for the sequel and ‘0’for the first release of a video game.

Genre of the video game. Controlling for the genre is important because there are differences in the evaluation of genres. Similarly to Cennamo’s and Santalo (2013) classification, we defined 7 groups of genres. However, contrarily to them we do not have the groups ‘Children games’ and ‘General’, and we combined all mixed and difficult-to-define genres of video games in the group “Others”.

Number of reviews. This variable reflects the number of critical reviews which form the basis for derivation of the aggregated product quality score. By controlling for the number of reviews, we account for popularity biases. The quality of video games with a low number of critical reviews may be biased or serve only as a subjective indicator of product quality.

Geographical location. The videogame developer's location may influence the access to production facilities, media networks, and consumer market. We allocated the firms that are from 46 countries to 3 categories according to their continental affiliation: North America, Europe and Other countries. Following this conditional separation, we created dummy variables.

Firms' age. This variable is calculated as a number of months that have elapsed between the foundation of the firm and the date of release of a certain product. There are 378 firms in our sample, with the oldest one aged 60 years. On average, firms are 12 years old.

Seasonality. This is a control dummy variable that reflects the time period within a year when the level of video game sales is relatively high. There is a sales peak in November and December, while over the rest of the year the level of sales is comparable. This variable has been also used in prior studies (e.g. Binken and Stremersch, 2009) which show that it is important to account for seasonality of sales because during the peak sales periods most of top video games are released, and a high number of top games might influence the assessment of the relative level of quality.

Promotional power of the video game publisher. Strong promotional capabilities of the video game publisher increase visibility of products. It does not necessarily mean that the visibility impacts reviewers' assessment of video games' quality. However, it may raise attention from a higher number of reviewers compared to less promoted products. To control for it, we use the number of published video games by a video game publisher before the promotion of each video game.

Estimation approach

To test our hypotheses, we applied ordinary least squares regression analysis. We ran the analysis in several steps which allow estimating in sequence direct effects and interaction effects of independent variables, and evaluate how they differ depending on the radicalness of technological changes that occur in the industry. In all models we included control variables.

We checked the dependent variable ‘Score’ for the presence of outliers and normality, and found it normally distributed (Skewness = -.332; Kurtosis = -.640). For the estimation of the interaction effect, both the moderator and independent variables were mean-centred before the analysis. We also excluded observations with Timing that exceeds 50 months, which led to a decrease of the sample size from 1082 to 940 observations. We excluded those observations because in the PC video game industry the average pace of emergence of radically new versions of DirectX is 12 – 18 months, and those products that are released on old versions of DirectX usually do not belong to the mainstream ones (indie video games), or belong to video game genres that are not affected by technological changes (puzzles).

Apart from it, we also checked independent variables for the presence of multicollinearity. The obtained maximum VIF value was 2.093 and the minimum value of tolerance was .478, which suggests that multicollinearity does not pose a problem in our study.

RESULTS

Hypotheses testing

The results of the analysis are presented in Table 3. Models 1-4 are estimated for the entire sample whereas Models 5-10 are estimated for the subsamples which include only radical (Models 5-6) or incremental (Models 7-10) changes. In Model 1, we added the independent variables (depth and breadth), the moderator (time-to-react) and control variables for all observations. In Model 2 we added the interaction variables (time-to-react×depth and time-to-react×breadth). Similarly to Models 1 and 2, we made the same steps in Models 7-8 but only for observations with incremental changes. In Models 3-4, 5-6 and 9-10, we run analysis with alternative specification of the independent variable (past depth of experience).

INSERT TABLE 3 ABOUT HERE

The analysis partly supports Hypothesis 1. The results of Models 7 and 9 show that depth of experience positively affects product quality when there are incremental changes with a positive and statistically significant direct effect of depth of experience (B = .646; p = .026) and past depth of experience (B = .376; p = .050). However, we do not find that depth of experience negatively affects product quality when there are radical changes in the industry. The statistically significant effect found for the entire sample (Models 1-2) and for the sub-sample of observations containing only incremental changes, disappears in the radical setting reflected in Model 5 (B = .270; p = .356).

Hypothesis 2, postulates that breadth of experience positively affects product quality when there are radical changes, but negatively when there are incremental changes in the industry. This hypothesis is not supported since breadth of experience is not statistically significant when there is an incremental technological change (B = -.007; p = .978) [Model 7], and when there is a radical technological change (B = -.466; p = .317) [Model 5].

As stated in Hypothesis 3, we find that the positive effect of depth of experience decreases with an increase in timing between the releases of new products by a firm. Model 2 shows that there exists a statistically significant negative impact of the interaction variable time-to-react×depth on product quality (B = -.041; p = .014), suggesting that product quality depreciates by .041 points for each extra month of waiting. Among the models based on the main specification, this is the only model where the interaction variable time-to-react×depth is significant.

As stated in Hypothesis 4, a prolongation of time spent on product development has a larger positive effect on product quality for firms with a greater breadth of experience. Models 2-4 show a statistically significant positive effect of the interaction variable time-to-react×breadth (B = .064; $p<.001$ and B = .052; $p<.001$, respectively), meaning that with each extra month of waiting firms with more breadth of experience benefit to a greater degree in terms of improving product quality. Moreover, in Model 6 (sample with only radical changes) the impact of this variable is even higher (B = .088; p = .003).

Using Preacher's technique of graphical representation of interaction effects[3], we plotted two graphs for both interactions (see Figures 1 and 2) using results from Model 2. The solid line stands for timing (time-to-react) of 1 month, the dashed line stands for timing of 21 months and the dash-dot line stands for timing of 48 months. Twenty one is the mean value of timing in our sample, 1 is a lower bound and 48 is an upper bound of this variable. From Figure 1 we can see that one month of waiting hardly impacts the positive effect of depth of experience, while 21 months decrease the effect significantly (Figure 1). At 48 months of delay the positive effect of depth of experience no longer exists. We can draw the opposite conclusions from Figure 2. The slopes show that firms significantly increase the product quality already at the level of timing being equal to 21 months. However, firms start benefitting from timing when the level of breadth of experience exceeds two. When the level of breadth of experience is lower than two, timing causes a negative effect on product quality.

INSERT FIGURE 1 ABOUT HERE

INSERT FIGURE 2 ABOUT HERE

The control variables show similar patterns in all 6 models. For example, the number of reviews has a positively significant effect on product quality score (B = .276; $p<.001$;

[3] http://www.quantpsy.org/interact/mlr2.htm

Model 2). Sequels, in general, have significantly higher scores than prequels (B = 3.262; $p<.001$; Model 2). Other control variables have no significant effect.

Sensitivity checks

In order to check how sensitive our results are with respect to methodological choices made, we ran a set of additional analyses. First of all, we included in the sample all observations with the timing values up to 60 months (initially it was 50 months) and acquired similar results (Model 11). However, when we increased the timing values up to 72 months we discovered that the significant interaction effect of time-to-react×depth variable disappears. This is consistent with the findings of Argote (1999) about the role of timing in knowledge depreciation. Secondly, we mean-centered the dependent variable 'product quality' separately for each year and ran the analysis with the new specification of the variable. In that way we could diminish the influence of unobserved annual changes in approaches to scoring of video games. The results were comparable; the only difference was a decrease in the significance of the direct effect of time-to-react (Model 12). Thirdly, we re-operationalized independent variables 'depth of experience' and 'breadth of experience'. The initial values of these variables were calculated using the information about products' versions of technologies (DirectX) that firms utilize during the release of their products. This information has been taken from the MobyGames database. The new values were based on the general information about the up-to-date technology available in the industry when the products have been released. We assumed that firms had indirect access to the information about new technologies and could enrich their experience even if they did not adopt those new technologies in their products. The analysis showed similar results (Model 13). However, the significance of the direct effect of depth of experience has decreased. This is due to the fact that the variability of the variable decreased since the frequency of the releases of DirectX exceeded the pace of releases of video games by a single company. The mean value of depth of experience in this case hardly exceeds '0.9'. Fourthly, in order to check whether the data are sensible to a change in the number of observation, we randomly excluded 40% of the observations and re-ran the analysis. The results were consistent with the results of the main sample (Model 14). The sensitivity checks for the samples with radical and incremental changes have shown similar patterns.

DISCUSSION

In this paper we study how firms' technological experience influences product quality. We conceptualize 2 types of experience. One reflects the extent of exploitation of a certain technology (depth of experience) whereas another one reflects the number of firm's encounters with different generations of technologies in the past (breadth of experience). Apart from estimating a direct effect of both types of experience on product quality, we investigate how they interact with timing of adoption of new technologies.

The study contributes, above all, to the following theoretical domains: the knowledge-based view, organizational learning theory, the dynamic capabilities view, and the first-mover advantage concept. Regarding the knowledge-based view, we provide an additional empirical prove of the positive role of intangible resources in shaping product quality, such as technological knowledge or technological experience. We also show that firms need to build different strategies for technological adoption depending on the richness of each type of experience they have.

This study also makes a significant contribution to organization learning theory. In their conceptual work that discusses research gaps and future perspectives for the development of organization learning theory, Argote and Miron-Spector (2011) stress the importance of studying the role of firms' knowledge as a function of experience. In our study we provide empirical evidence in support of Argote's and Miron-Spector (2011) hypothesis that firms learn from experience which influences intra-firm changes and performance. While doing it, we rely on longitudinal and time-series data following Argote's and Miron-Spector (2011) argument that learning occurs over time. As suggested by the authors, we measure experience as a cumulative number of products released by firms and estimate its effect on non-financial performance (product quality) as an indicator of effectiveness of the learning process.

The results of our study also support the claim of Argote (1999) that knowledge depreciates over time and firms do not benefit from the acquired knowledge after 5 years. In particular, we find that technological experience and accumulated knowledge have significantly positive influence within the first 6 years following the emergence of a new technology, but after 6 years the effect disappears. However, in contrast to Argote (1999) and other studies showing that recent experience is more valuable for firms than more distant past experience (Argote and Miron-Spector, 2011; Argote et al., 1990; Benkard, 2000), we only find depreciation of the positive effect of experience acquired via encountering incremental technological changes (extensive exploitation of one certain technology), as opposed to the experience from radical changes.

The depreciation of the effect of depth of experience can be explained by the fact that firms reach a certain technological limit with a growing number of released products based on the same technology and cannot learn anything new from the current or an incrementally new technology. In addition, any new knowledge which firms gain from the exploration of a given technology may depreciate the value of already exiting knowledge and experience. Finally, the returns to knowledge might also decrease when a large number of companies on the market are exploiting the same technology.

In contrast to the depth of experience, the effect of breadth of experience doesn't depreciate fast but continue influencing firms' performance when it increases. We did not find a significant direct effect of breadth of experience but we found a positively significant interaction effect of timing and breadth of experience on product quality. This implies that having higher breadth of experience does not reflect on the product quality per se. Its effect largely depends on the correctly chosen timing strategy: firms with higher breadth of experience benefit more from timing than firms with lower breadth of experience. A plausible explanation of such a finding is that experience with numerous technological changes allows firms to comprehend how to benefit from them and how to adjust their routines and capabilities to a new technological reality. However, the optimal use of technologies comes with learning that implies timing.

On the one hand, these results contradict the general assumption that recent experience is more valuable than distant past experience (Argote et al., 1990; Benkard, 2000). On the other hand, they support the theoretical assumption that knowledge, acquired from different types of experience, depreciates differently (Madsen and Desai, 2010) and that different types of experience may affect firms' learning process and performance in different ways (Argote and Miron-Spektor, 2011). This could be a valuable contribution to the part of organizational learning literature that is focused on studying depreciation of experience.

Apart from the knowledge-based view and organization learning theory, this study provides new implications for the dynamic capabilities view. There are on-going debates in the academic literature regarding the appropriate conceptualization and measurement of the dynamic capabilities. One of the main 'stumbling blocks' is whether to consider dynamic capabilities as routines that allow adjusting to a changing environment or capabilities to change the routines. This is in a way a semantic disagreement but one thing is certain - dynamic capabilities mean the ability of firms to adjust to changing environment. Our study provides strong evidence that firms may improve their performance when they encounter sequential radical technological changes. In addition, firms benefit directly from depth of experience when there are incremental changes. These findings support Zahra et al. (2006) separation of substantive capabilities and dynamic capabilities.

Elaborating a bit more on this topic, Salvato and Rerup (2011) claim that repetitive activities help to develop and improve routines. Depth of experience in our study reflects the repetitive use of one certain technology and, thus, it also reflects the utilisation of the same routines during the process of production. This fact allows us to consider depth of experience as a good proxy for the measurement of routines or substantive capabilities. In contrast, breadth of experience reflects the number of different generations of a technology faced by firms and, hence, it shows the number of events which forced firms to adjust or alter their activities. We believe that the nature of breadth of experience reflects firms' abilities to cope with technological changes and adjust to a changing technological environment. This, in turn, allows us to consider breadth of experience as a good proxy for the measurement of dynamic capabilities. By providing a solution of how both types of capabilities can be operationalized, our study contributes to the theoretical domain of the dynamic capabilities view literature,.

Finally, by providing some evidences that firms may benefit from the late adoption of new technologies when they have an extensive breadth of experience, the study contributes to the first-mover advantage concept. As discussed above, when there is a radical technological change those firms with extensive breadth of experience may effectively delay the release of a new product based on the new technology until the quality of this product corresponds to the customers' expectations. It means that a superior product quality and customers' satisfaction are achieved not via instant adoption of a new technology and release of a new product but via learning, elaborative experimentation and utilisation of a new technology. All these actions require a proper timing of product's release that would allow effective utilization of a new technology without a threat of being outrun by competitors.

Our study also shows that there is a negative statistically significant direct effect of timing suggesting that in order to benefit from a new technology firms have to adopt this technology as fast as possible. Inconsistencies in the direct effect of timing, on the one hand, and the interaction effect of timing and breadth of experience, on the other hand, allows concluding that experienced and inexperienced firms need to follow different product development strategies. Given that firms with extensive breadth of experience benefit more from timing, one might conclude that new entrants would definitely lose in competition with incumbents if they try to follow the same timing strategy. The lack of experience will not allow newcomers to apply the same routines for product development as incumbents do during a radical technological change. This also involves a learning process when a new technology emerges. Experienced firms, who understand the complexity of new technologies, spend more time for learning and experimentation in order to achieve the highest product quality. Contrarily, less experienced firms, who lack technological experience, act opportunistically and adopt a new technology faster, hoping to benefit from its higher performance compared to the prior technology.

The uniqueness of the study also manifests itself in taking video game industry as a setting for the empirical analysis. In manufacturing industries, firms postpone the adoption of new technologies or materials until costs for this adoption decrease and benefits from the release of a new product exceed the losses from cannibalization of prior products (Fisch and Ross, 2014). Contrarily to other manufacturing industries, in video-game industry, timing for adoption of new technologies does not depend on the financial ability of firms to cover the costs of new materials. Video game developers spend time only for effective utilization of all new features proposed by a new technology. From this perspective, the analysis based on video game industry provides better insights on how timing interacts with firms' experience.

The results of this study are not only interesting from the theoretical perspective but are also valuable for practitioners. None of managers wish to spend firm's recourses on developing products that do not meet customers' expectations. Using the results of our study, managers may define the major radical and incremental technological changes within their industry and apply our approach to estimate the level of their own technological experience and expertise of their competitors. This evidence, in turn, may help them to understand how flexible their firm is with respect to the timing of adoption of a new technology. The results also may assure practitioners of experienced firms that the time that they spend for learning and mastering of a new technology brings more benefits than the fast integration of the new technology in products.

In addition to what is done in our study, it would also be interesting to investigate the effects of diverse types of experience (e.g. technological; market; alliances; social changes and other business related types) on product quality. In particular, one could analyse what types of experience are the most valuable for firms, what types of experience can be harmful under certain conditions, and what helps to avoid or lessen the negative impact of such experiences. We leave these questions for future research.

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Table 1 The main innovations and differences between the most significant versions of DirectX

Version of DirectX	The main innovations	Short description (remarks)	Additional iterations
DirectX 1.0	Enable playing video games on Windows OS	There were no such applications before. The main prior platform was MS-DOS	n/a
DirectX 2.0	Direct3D (D3D)	Technology that allowed rendering 3D graphics. DirectX became more functional, the main components of pipeline technology were created	2.0a
DirectX 3.0	Some incremental improvements of the previous version		3.0a, 3.0b
DirectX 4.0	Never released		n/a
DirectX 5.0	Simplification of programming code, no radical changes	The application became more user- (developer-) friendly.	5.2
DirectX 6.0	Multitexturing and simplification of programming language	Application of multiple textures on 1 polygon was introduced to improve quality of 3D visualisation	6.1, 6.1a
DirectX 7.0	hardware-accelerated T&L (Transform and Lightning) technology; new format of textures (.dds)	Redirection of 3D processes specifics from central processor to graphic card was made.	7.0a, 7.1
DirectX 8.0	Shader Model 1.1	Ability to create different visual special effects (e.g. mist, fire, sea surface etc.)	8.0a, 8.1, 8.1a, 8.1b, 8.2
DirectX 9.0	Shader Model 2.0; High Level Shader Language (HLSL); support of Multiple Render Targets (MRT) technology; Multiple-Element Textures (MET) technology	HLSL is a language that allows more efficiently programme shaders; MRT improves multiple rendering; MET enables application which makes it possible to use one or more of the elements as a single-element texture - that is, as inputs to the pixel shader.	9.0a, 9.0b, 9.0c
DirectX 9.0 c	Shader Model 3.0	Improvement of functionality of Shader Model	
DirectX 10.0	Shader Model 4.0	Improvement of functionality of Shader Model, improvement of HLSL language	10.1

DirectX 11.0	Shader Model 5.0; support of tessellation and redesign of the rendering pipeline	Tessellation means that the quality or dimensions of 3D objects is not constant but changing depending on the distance between the camera and the object	11.1, 11.2

Table 2. Descriptive statistics and Correlation matrix

	Variable	Minimum	Maximum	Mean	Std. Dev	1	2	3	4	5	6	7	8
1	Score	50.27	95.48	74.8589	9.87370	1							
2	Depth of experience	0	12	1.13	1.685	.044	1						
3	Depth of experience (past)	0	17	.49	1.117	.060*	.742**	1					
4	Breadth of experience	1	9	2.49	1.624	.100**	.388**	.487**	1				
5	Timing	0	59	24.65	17.016	-.127**	.422**	.340**	.150**	1			
6	Number of reviews	1	89	18.35	14.373	.381**	-.101**	-.026	.063*	-.061*	1		
7	Age	12	725	146.51	80.9	-.044	.185**	.235**	.458**	.102**	-.089**	1	
8	Promotion Power	1	410	131.29	133.669	.158**	.173**	.241**	.324**	-.071*	.112**	.155**	1

N = 1082; * P<.05; ** p<.01

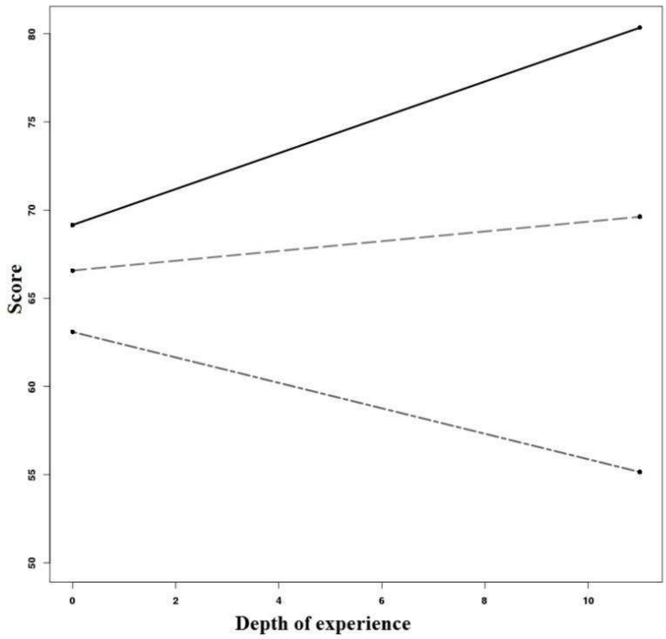
Table 3. Results of the regression Analysis for Quality of products

Predictors	All observations		All observations (past depth)		Observations for radical changes (past depth)		Observations for incremental changes		Observations for incremental changes (past depth)		Sensitivity Analyses			
	Direct effects (Model 1)	Interaction effects (Model 2)	Direct effects (Model 3)	Interaction effects (Model 4)	Direct effects (Model 5)	Interaction effects (Model 6)	Direct effects (Model 7)	Interaction effects (Model 8)	Direct effects (Model 9)	Interaction effects (Model 10)	Interaction effects (Model 11)	Interaction effects (Model 12)	Interaction effects (Model 13)	Interaction effects (Model 14)
Constant	68.865***	68.713***	68.931***	68.411***	65.910***	65.707***	69.410***	69.261***	69.467***	69.152***	69.335***	-2.525*	67.435***	69.683***
Depth of experience	**.915*** **	**.997*** **	**.396***	**.131**	**.270**	**.191**	**.646***	**.593†**	**.376***	**.083**	**.785*** **	**.932*** **	**.142**	**1.307*** **
Breadth of experience	**-.071**	**-.134**	**-.044**	**-.055**	**-.466**	**-.058**	**-.007**	**-.168**	**-.115**	**-.174**	**-.111**	**.010**	**.073**	**-.144**
Timing	**-.127*** **	**-.119*** **	**-.110*** **	**-.102*** **	**-.133*** **	**-.062**	**-.131*** **	**-.130*** **	**-.128*** **	**-.134*** **	**-.072*** **	**-.048***	**-.082*** **	**-.108*** **
Interaction time-to-reactXbreadth		**.064*** **		**.052*** **		**.088*** **		**.060*** **		**.050*** **	**.051*** **	**.067*** **	**.045*** **	**.064*** **
Interaction time-to-reactXdepth		**-.041***		**.005**		**.010**		**-.024**		**.008**	**-.027***	**-.037***	**-.018†**	**-.041***
Sequel	3.183***	3.262***	3.347***	3.553	2.494**	2.596**	3.309***	3.433***	3.397***	3.605***	3.078***	3.411***	3.756***	3.151***
Number of reviews	.272***	.276***	.262***	.266***	.353***	.365***	.237***	.240***	.236***	.237***	.275***	.281***	.278***	.277***
Age	-.005	-.004	-.005	-.004	-.012†	-.012†	.001	.001	.001	.001	-.004	-.002	-.003	-.007
Seasonality	-.249	-.156	-.317	-.121	-.573	-.287	.068	.213	.060	.309	-.050	-.069	.091	-.882
Promotion Power	.004	.004†	.004	.004	.009*	.009*	.002	.002	.001	.002	.003	.004	.004	.006
R Square adjusted	.218	.232	.221	.223	.329	.344	.168	.180	.166	.177	.223	.222	.228	.245
Number	940	940	940	940	320	320	620	620	620	620	1082	940	940	596

†P<.1; * p<.05; ** p<.01; *** p<.001

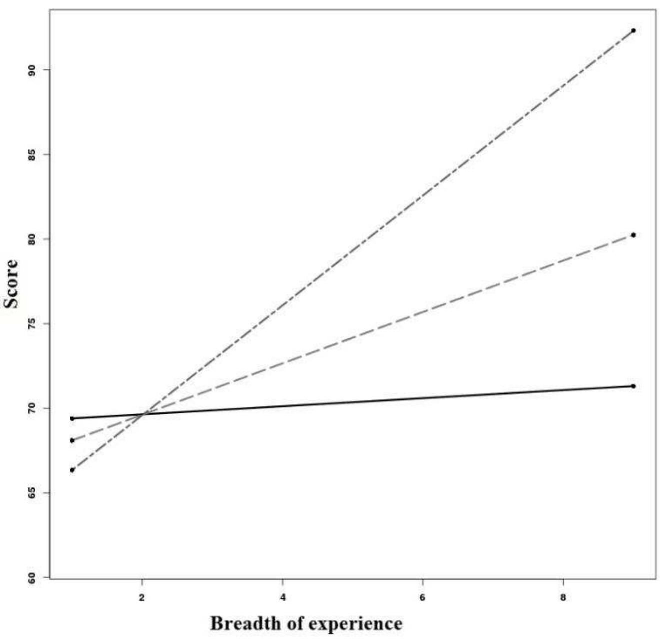
All reported coefficients are unstandardized.

Control dummy variables which reflect genres and geographical location were included in the model but excluded from Table 3 in order to make it easy to read



Solid line - Timing of 1 month,
Dashed line - Timing of 21 months
Dash-dot line - Timing of 48 months

Figure 1 Interaction for time-to-react×depth



Solid line - Timing of 1 month,
Dashed line - Timing of 21 months
Dash-dot line - Timing of 48 months

Figure 2 Interaction for time-to-react×breadth