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Multidimensional experience and performance of highly skilled administrative staff: Evidence from a technology transfer office

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ABSTRACT

Experience defined in terms of time, scope, type, density and timing affect performance of highly skilled administrative staff. We apply a multidimensional model to the field of science commercialization as a typical multi-goal oriented process. We identify how different conceptualizations of experience models lead to diverse conclusions regarding their effects on facets of performance such as speed, efficiency and revenue. Acknowledging multifaceted goals of science commercialization, we further contribute to the body of work on individual level factors regarding universities' commercialization performance. In this paper we provide evidence from the context of universities' commercialization efforts, relying on administrative records of a Japanese university including 845 transfer cases over a 13-year period (2004–2016). By focusing on coordinators working in a technology transfer office, and the various measurement modes of their experience, we detect several important characteristics. While several experience components affect speed and efficiency of technology transfer, our results show that revenue is determined by interaction components.

1. Introduction

Universities play a critical role in economic and societal development through their education, research and commercialization efforts (Bercovitz and Feldman, 2006; Etzkowitz and Leydesdorff, 2000; Klofsten et al., 2019; Perkmann et al., 2013). There is an ever-growing corpus of studies addressing various aspects of entrepreneurial universities' efforts (Forliano et al., 2021; Noh and Lee, 2019), also on factors influencing universities' commercialization performance (Chapple et al., 2005; O'Kane et al., 2021; Riviezzo et al., 2019).

Our focus is on a particular internal individual factor related to human capital: the influence of IP coordinators' experience on the results of licensing of university technologies – one of the key science commercialization activities. Internal factors, i.e. organizational level factors (Novotny, 2020), including those related to human capital, have been studied before in terms of commercialization performance (Hsu et al., 2015). Literature in this field is however more focused on the role of other actors related to science commercialization (Noh and Lee, 2019), while often overlooking technology transfer office staff.

Intellectual property (IP) coordinators, working at technology transfer offices, are one of the pivotal actors in commercialization efforts. They work in a sphere where academia and industry interests meet, and strive to commercialize university inventions (Micozzi et al., 2021; Owen-Smith, 2011), also via technology transfers. Even though there have been attempts to understand what technology transfer offices are 'capable of' through various conceptual lenses such as capabilities, competence, practices, expertise and even experience (Weckowska, 2015; Micozzi et al., 2021), relatively little is known about how factors connected to individual staff members play out. In line with recent calls to understand more about how the characteristics of these individuals can affect the course of technology transfer processes (Villani and Phillips, 2021), we aim to investigate if and how the different dimensions of individuals' experience can affect their results, and overall commercialization performance.

Human capital theories suggest that individuals possessing greater levels of knowledge and skills – which result from experience – tend to achieve better results (Becker, 1964; Marvel et al., 2016; Ployhart and Moliterno, 2011; Unger et al., 2011). Similarly, organizational research and innovation studies emphasize that individuals' knowledge and skills are mainly the product of their experience (Nonaka, 1994; Solheim et al., 2020). We adopted the idea that conceptualization of experience should be understood as multidimensional in nature (North, 2019;

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Quinones et al., 1995; Tesluk and Jacobs, 1998; Van Iddekinge et al., 2019) in contrast to works relying on a single dimension of experience, e.g. individuals' tenure (McDaniel et al., 1988). However, we took into account clear indications that not all experience dimensions necessarily lead to better performance (Nass, 1994).

The interplay of experience and performance is even more complex when organizations and their employees pursue several diverse performance goals. This is the case in entrepreneurial universities, wherein TTOs need to manage these different goals. The quantitative commercialization goals, which lie at the heart of our analyses, span from seeking additional revenues, i.e. goals related to lucrativeness, to pursuing goals dictated by the university's public service and knowledge dissemination mission (Graff et al., 2002; Jensen and Thursby, 2001), and seeking to create societal impact (Fini et al., 2018). The aim of technology transfer office staff is to pursue these various goals (Fitzgerald and Cunningham, 2016). We focus on the speed, efficiency and revenue generation as being indications of successful university technology transfer operations via licensing, and concurrently the performance goals of individual TTO staff.

We construct three multidimensional experience models, each focusing on a specific facet of successful performance in multi-goal oriented organizations (Fig. 1), building upon prior literature on experience that revealed its breadth and complexity, and identified its multidimensionality. Following a multidimensional experience model approach (Quinones et al., 1995; Tesluk and Jacobs, 1998), we explore whether different experience modes – i.e. those of time, scope, type, density and timing – of highly experienced administrative staff, i.e. the IP coordinators, lead to diverse outcomes regarding their effectiveness on multifaceted commercialization performance.

Based on experience and science commercialization literature we, *firstly*, apply the multidimensional experience model to the field of science commercialization. By applying the multidimensional lens to experience we contribute to further construct clarity of experience inside the science commercialization field, explicating the “type” measurement mode of experience as networking experience, due to the brokering nature of IP coordinators' work (Comacchio et al., 2012; Grzegorczyk, 2019; Vogel and Kaghan, 2001). This can also be applied to other profiles in brokering roles. *Secondly*, we revise and extend the previous multi-dimensional experience models by Quinones et al. (1995) and Tesluk and Jacobs (1998) both in terms of including active and passive mode types (which account for the strength of the experience), and by adding to the existing set of contextual factors (including so-far in experience literature neglected object level contextual factors). *Thirdly*, we illustrate that differently conceptualized models of experience can lead to diverse conclusions regarding their effects on science commercialization performance. Positive effects are typically expected in regard to performance, but we also show some modes of experience do not translate into higher performance, e.g. in terms of lucrative deals. *Fourthly*, by providing a multidimensional conceptualization of experience and acknowledging multiple goals of science commercialization, we contribute to a more nuanced understanding of the role of individual level factors regarding universities' commercialization performance. Thereby we contribute to the lacking area of micro-foundational analyses which can lead to a better understanding of the role of intermediaries and the workings of the technology transfer offices (O'Kane et al., 2015; Noack and Jacobsen, 2021; Villani and Phillips, 2021). This individual level focus also allows us to gain more insight into potential bottlenecks and solutions thereof, thus enabling us to provide management level recommendations.

This paper is a response to calls for further examination of relationships between work experience and performance (Quinones et al., 1995; Sturman, 2003). We use a dataset from a top Japanese research university, where licensing (including assignment) transfer cases were explored. The dataset is derived from internal administrative data, merging inventions, patents, licensing data, human resources records and survey data. By capturing IP coordinators' experience levels and discovering changes in their workload over time (i.e. reallocating licensing cases between IP coordinators) we undertake a unique exercise in this field.

2. From multidimensional experiences to multifaceted performance outputs of highly skilled administrative staff

2.1. The experience-performance nexus in multi-goal settings

Human capital theory was originally developed to explore the value of education, but soon extended to include the skills derived from experiences (Becker, 1964; Marvel et al., 2016). This theory typically posits that experience can, and mostly does, shape individuals' skills, expertise, and decisions (Marvel et al., 2016; Unger et al., 2011), as well as increasing their ability to handle task-complexity (Quinones et al., 1995). This is reiterated also in works on organizational research and innovation studies (Nonaka, 1994; Solheim et al., 2020).

Experience plays a central role within work performance models

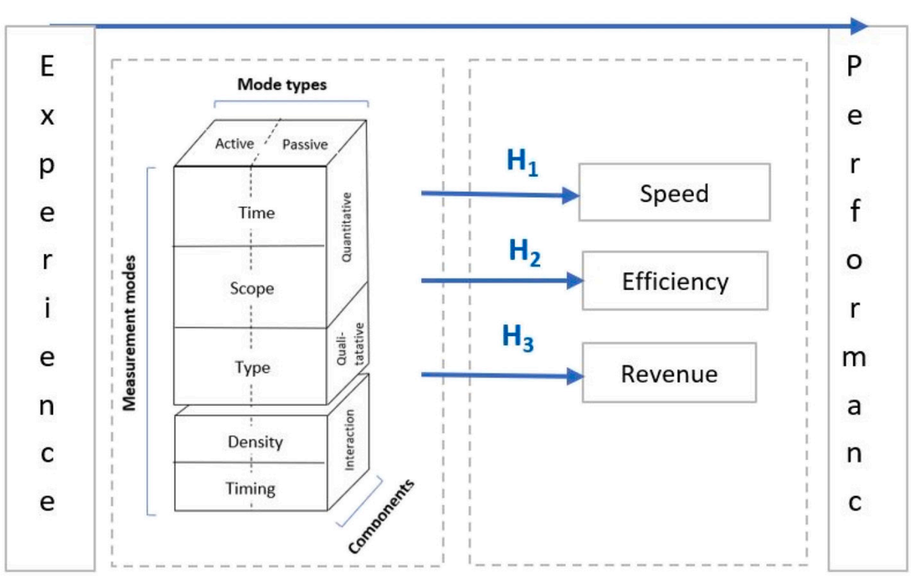

Fig. 1. Multidimensional experience and multifaceted performance.

(McDaniel et al., 1988; Medoff and Abraham, 1980; Quinones et al., 1995). This follows the suggestion of both conventional wisdom, and many studies in the field, that more experience should lead to a better performance (Dokko et al., 2009; Sturman, 2003; Unger et al., 2011). Based on this stream of literature, uncertainty should only remain as to the magnitude of the relationship (Unger et al., 2011). However, while trying to uncover the multidimensional experience-performance nexus in multi-goal settings, we allow for heterogeneity, since another stream of literature highlights that more experience always leading to higher levels of performance still eludes sound empirical proof (Baron and Henry, 2010; North, 2019; Sturman, 2003; Ucbasaran et al., 2009) in any setting. The adopted multidimensional conceptualization of experience, can enable us to detect that some types of experience contribute to results, while other types of experiences may even impede them or have no effect, suggesting unforseen conclusions in terms of the effects of experience on performance (Avery et al., 2003; Donegan et al., 2019; Nass, 1994). In this line Radaelli et al. (2018) show that highly skilled individuals can replicate routines and tactics more readily in pursuit of some outputs, compared to others. These can be especially related to outputs where the effects of experience can be 'softened by external conditions'. This could be especially relevant in multigoal settings, such as the TTO.

In this work we explore whether the observed dimensions of experience affect all facets of performance included in the model, while using the multi-goal context of science commercialization, or more specifically using the IP coordinators as model highly skilled administrative staff. We follow a multidimensional conceptualization of experience (Dierdorff and Surface, 2008; North, 2019; Quinones et al., 1995; Tesluk and Jacobs, 1998; Van Iddekinge et al., 2019), in contrast to more used one-dimensional approaches, e.g. experience being mirrored in the amount of times an individual has engaged in a certain task (Madiedo et al., 2020) or through the time dimension, e.g., time spent on particular tasks, or working for an organization (Takeuchi et al., 2019).

2.2. Individual level experience and highly skilled administrative staff

Unlike many of the prior studies of experience, we focus on the role of experience on the individual level. McDaniel et al. (1988) describe the highly skilled individuals in terms of performing high-complexity jobs. However, the highly skilled administrative staff is also constrained by the system they belong to, consequently operating within a 'framework of limited choices' (Cardozo et al., 2011). Sturman (2003) reveals in his meta-analysis experience being more related to performance in high-complexity jobs compared to low-complexity ones.

Experience can be relevant on an individual level (Dokko et al., 2009), *meso* level of teams or units (Lawrence, 2018; Nass, 1994), as well as organizational level (Eggers et al., 2020), but there is less emphasis on the individual level. Prior studies that have taken into account the multidimensional nature of individuals' experience have been conducted especially in relation to leaders (Avery et al., 2003; Radaelli et al., 2018) or entrepreneurs (Baron and Henry, 2010). The multidimensional experience-performance nexus of highly skilled individuals remains relatively underexplored – with some exceptions, e.g. Cockburn et al. (2002) examined the experience-performance nexus of another highly skilled occupational group, the patent coordinators - although they can be of particular interest. Such individuals can affect outcomes to a large degree and a deeper understanding of the mechanisms at play could serve as guidance for managers and policymakers alike.

2.3. Role of IP coordinators' experience in a multi-goal technology transfer office setting

Initially, technology transfer offices (TTOs) were created to safeguard and manage universities' intellectual property and to provide additional funding by transferring the rights to use university-owned IP to firms (Feldman et al., 2002). They were typically seen as (organization level) technology transfer brokers (Vogel and Kaghan, 2001). This understanding has broadened over the years (Noack and Jacobsen, 2021) and new goals have been recognized as relevant in the context of TTOs (Bozeman et al., 2015; Giuri et al., 2019; Sterzi and Martínez, 2019). The TTO's goals are to be aligned with the university's public service and knowledge dissemination mission (Graff et al., 2002; Jensen and Thursby, 2001), and with the university goals related to creating societal impact (Fini et al., 2018). Universities may have their preference in terms of goal(s). Some universities are more dedicated to dissemination and impact seeking goals, contributing to local development. Others, especially more specialized and high prestige universities, are seen as more oriented toward income generation (Giuri et al., 2019), i.e. goals related to lucrativeness.

The TTO's multiple goals, which they also pursue through one of their main activities – licensing – implies an additional level of complexity when trying to understand whether diverse experience levels might lead to increased achievement of goals, in terms of successful licensing. In this article we focus on licensing, since, from the social perspective, it allows for technology dissemination via commercialization and impact generation. From the revenue generating perspective, a license provides the legal foundation for appropriation (including the creation of a revenue stream).

Micozzi et al. (2021) have recently pointed out to the debates about the importance of the staff at TTOs. According to Novotny (2020) factors such as experience, skills and capabilities affect performance outcomes of technology transfer. Similarly, Owen-Smith (2011) and Siegel et al. (2003) believe that outputs depend heavily on skills, expertise and decisions of licensing professionals, i.e. IP coordinators. This is also in line with recent suggestions by Villani and Phillips (2021) that inside technology transfer the characteristics of intermediaries (including their experiences) can also determine the course of a transfer process. Nonetheless, also other factors can matter, although we are still struggling with consolidating the often divergent conclusions regarding their importance for performance (for organizational level factors compare e. g. Bozeman et al., 2015; Clarysse et al., 2011; Wu et al., 2015).

In contrast to our work, previous studies in the field of science commercialization that take into account experience focus mainly on knowledge producers, i.e. academic researchers and their teams (e.g. Bercovitz and Feldman, 2011; Clarysse et al., 2011; Modic and Yoshioka-Kobayashi, 2020; O'Kane et al., 2020), company-university collaborators (Steinmo and Rasmussen, 2018), or specific entities, such as technology scouts (Noack and Jacobsen, 2021). There is also a large focus in the literature on TTOs as monolithic actors and the effect of their staff's combined experience on science commercialization outputs (Chapple et al., 2005; Micozzi et al., 2021). We investigate whether the experience of highly-skilled individuals, the IP coordinators, working in brokerage positions affects commercialization outputs, building on the assessments that individuals working at TTOs should be able to benefit from some types of experiences (Kloke and Krueken, 2010; Siegel et al., 2004; Zheng et al., 2013).

This article focuses on IP coordinators working in a sphere where academia and industry interests meet, where they strive to commercialize university inventions. They fit the definition of highly-skilled individuals working in multi-goal organizations. IP coordinators have been described as a profession in the making (Owen-Smith, 2011) as long as a decade ago, yet we still have limited insight into their attributes. IP coordinators have limited influence on the production of technologies (Cardozo et al., 2011), however they can, to a large extent, influence the after-disclosure commercialization process. After the invention disclosure process takes place, most decision-making, albeit influenced by other actors, is left to TTO personnel. This makes individual IP coordinators pivotal actors in technology transfer processes. Nevertheless, science commercialization is also an administrative process, and IP coordinators, just like other highly-skilled administrative workers, are faced with a limited choice framework (Cardozo et al., 2011). The analysis of individual actors, i.e. IP coordinators, allows us to discover a more nuanced understanding of factors contributing to heterogeneity in terms of technology transfer performance (see Wu et al. (2015) and literature therein).

2.4. How does individuals' multidimensional experience shape diverse commercialization outcomes? Developing hypotheses

We address the question of whether different experience dimensions lead to diverse outcomes regarding their effectiveness on multifaceted commercialization performance via three hypotheses. Each hypothesis is related to one of the performance facets, in terms of speed, efficiency and revenue generation (see Fig. 2.).

Following a triadic model proposed by Quinones et al. (1995) describing three measurement modes – time, amount and type – we first considered highly skilled individuals' experience in terms of time, scope and type as the *main measurement modes*. The first two capture what Tesluk and Jacobs (1998) understand as *quantitative components*, and the last as *qualitative component*; the latter being directed more toward the quality of the experience, i.e. managing complexities. Albeit prior literature seems to suggest that qualitative components might be more relevant in terms of experience-performance nexus, Van Iddekinge et al. (2019) in their meta-analysis discover that both types of components are similarly strong, at least when considering pre-hire experience. We adopted measures (i.e. measurement modes) to capture this multidimensional experience; thus, time-based measures would capture time passed, amount measures (i.e. scope) are based on how many times a task has been performed or the frequency of achieved outcomes, and type measures would encompass the qualitative nature of experience, in our case networking experience, since IP coordinators are typical brokers (Vogel and Kaghan, 2001). Furthermore, we add, based on the Tesluk and Jacobs' (1998) upgrade of the Quinones model, another component, the interaction, with two more additional measurement types: density and timing.

We also add another layer to our model, i.e. the mode type, indicating the active or passive mode types. These account for the strength of experience and can be applied to all measurement types included in the model. Related to time we can either take into account the whole tenure (which would be a passive mode type) or vice-versa we can only account for time since they have started with their job activities, by engaging in learning by doing (active mode type). Similarly, for amount, we can observe only activities with (positive) results (active mode type), or vice versa, take into account also all that have a potential for (positive) results.

We turn now to the individual experience measurement modes. Experience is inherently tied to *time*, whose passage allows for the accumulation of job-related knowledge and experience (Quinones et al., 1995; Sturman, 2003). There are two competing theories on how time affects employees (Mann, 2013). On the one hand, as time passes, employees learn more about their tasks and become more skilled. However, the acquisition of tacit knowledge might be the cause of an increasingly rule-bound (and thus less vigilant) approach to tasks (Dokko et al., 2009). In line with the former, the so-called 'experience trap' (Hahn and Kim, 2021) has been previously detected for individuals in decision-making positions, in particular for executives. In general, the length of experience should have a positive effect on outcomes, however from the rule-bound perspective, the seniority of an IP coordinator might mean they have a more rigid approach to tasks.

Quinones et al. (1995) point out that it is somewhat less common for studies to measure experience as an amount, i.e. its *scope*. Previous successful cases enrich individuals' human capital and affirm useful knowledge and heuristics used also for subsequent tasks (Radaelli et al., 2018). But cases that only have a potential for (positive) results (passive mode type) should be taken into account, i.e. including error-ful trials, since learning by doing can envelop also a trial-and-error learning (Reese, 2011). This is also in line with some indications that also completing other similar tasks can be a part of learning by doing (Schilling et al., 2003). This type of learning can thus come also from cases where the potential was in the end unexploited, yet an individual

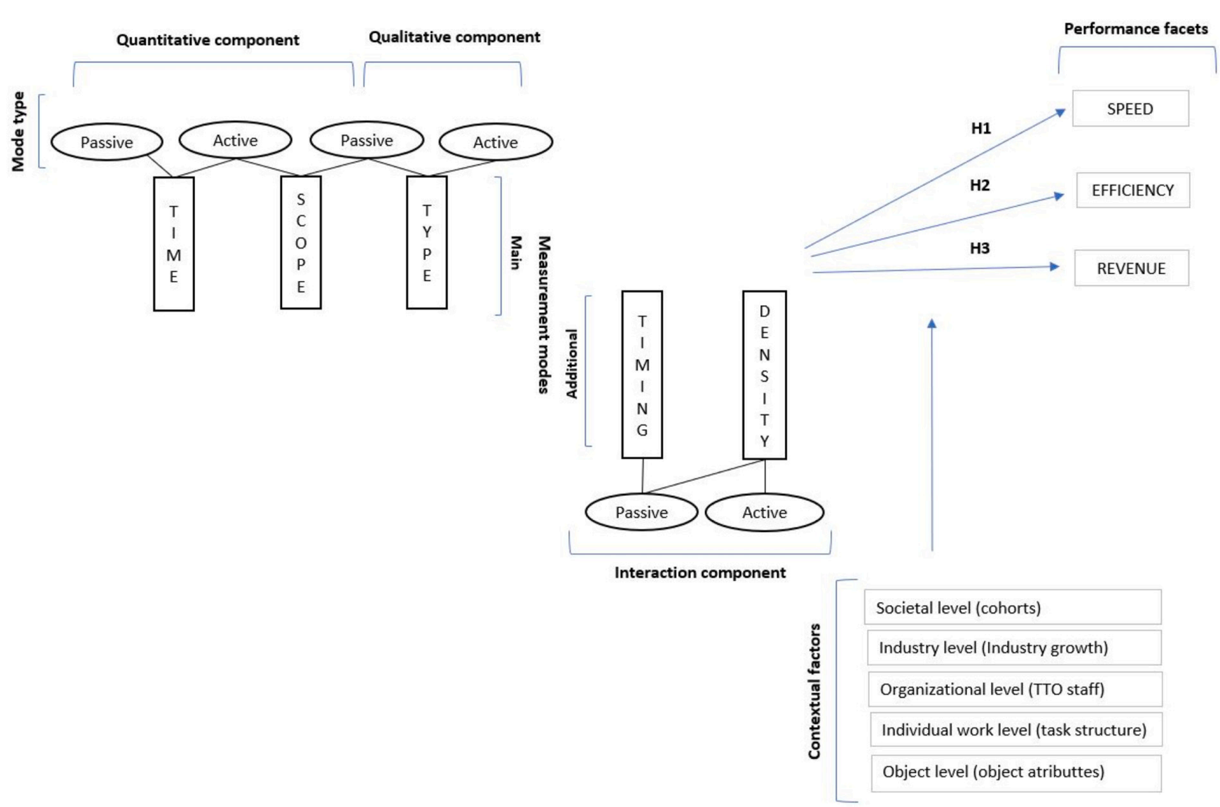

Fig. 2. Multidimensional experience and multifaceted performance.

had the opportunity to learn from the activity itself. The latter is also in line with the science commercialization literature, showing that coordinators improve their capabilities by experimenting - which includes failures (Debackere and Veugelers, 2005; Zheng et al., 2013).

We focus on networking as a *type* measure, which is another experience-inducing element. Quinones et al. (1995) understand the type dimension as related to complexities, while the very essence of working as brokers entails managing social complexities. Inside technology transfer processes it is important that relevant networks are built up, so that the actors have sufficient social capital (Grzegorczyk, 2019). Networking is thus one of the key areas of expertise of IP coordinators, since the IP coordinators as brokers need to leverage also their networking experience for technology transfer (Comacchio et al., 2012). An experienced IP coordinator is more likely to have developed relevant networks with other actors. Engagement via established relationships can conceivably influence the volume of transfers processed and the speed of reaching subsequent agreements, thereby positively influencing individuals' efficiency. In the science commercialization literature, some emphasize that technology commercialization flows more rapidly, smoothly and with less resistance along existing ties and channels leading to the earlier initiation of technology transfer negotiations; they point out the familiarity element between contracting parties which may accelerate negotiation, and understand its execution as a result of the established trust previously built as well as the capitalization of routines developed in previous interactions (Bercovitz et al., 2019; Owen-Smith and Powell, 2004).

According to Tesluk and Jacobs (1998) the interaction component is comprised of density and timing. *Density* is capturing the intensity of the experience within a certain timeframe. Quinones et al. (1995) mention a developmental punch, referring to individuals experiencing periods of high intensity. Tesluk and Jacobs (1998) postulate that if inside the same year one person repeatedly faces more challenges (in our case challenges presented by the complex task of licensing) than another one, the experience in the first scenario would exhibit greater density (active mode type). Furthermore, the total workload (including both patenting and licensing) within a certain timeframe, can also exhibit different levels of density (passive mode type). Lastly, *timing* refers to an event that occurs within a longer sequence (Tesluk and Jacobs, 1998). In line with the imprinting theory (Simsek et al., 2015) one should focus on the initial period, and within this observe when the first event occurs, i.e. when the individual first engages with their job tasks. Similarly the literature on work performance indicates that this initial time (induction period) is very important.

Due to entrepreneurial universities pursuing multi-goal strategies in terms of technology transfer, we then separately focused on three quantitative performance facets of successful licensing: *speed*, *efficiency* and *lucrativeness of licensing*, and constructed our models. TTOs need to manage those different goals, which requires them to be responsive to stakeholders with a variety of needs and expectations: e.g., not only in terms of academic and commercial aims as pointed out e.g. by O'Kane et al. (2015), but there is also variety in terms of commercial performance goals. Performance indicators, such as those related to simply counting the numbers of successful events (e.g. number of patents and licenses), are often used when trying to understand the performance of technology transfer in general (O'Kane et al., 2021), as well as in particular as related to TTO staff (Micozzi et al., 2021; Zheng et al., 2013). Similarly, revenue related performance goals were taken into account before as related to TTO staff (e.g. Micozzi et al., 2021). When attempting to understand the value of failed experiences for IP Coordinators, Zheng et al. (2013) initially considered the scope and revenue performance indicators, however they only analyze the effects in terms of scope. They do so, since the focal organization explicitly stated that their mission is related to dissemination. Our preliminary interviews however showed that a multitude of goals are seen as relevant by the staff in our focal organization. Furthermore, the literature on job performance also points out the importance of efficiency, and of timeliness (Bernardin and Beatty, 1984), which we take into account.

Speed, the ability to compress time, is a unique capability that may confer a sustainable competitive advantage (Kessler and Chakrabarti, 1996). In terms of science commercialization, less time spent negotiating a license means more time for companies to exploit the technology while under patent protection. Longer time delays may frustrate licensees and undercut the university's reputation as a viable technology transfer partner (Bercovitz et al., 2019). Link and Siegel (2005) also point out that university managers tend to stress the importance of time to market and the related first mover advantages. A faster transfer process increases the possibility of successful licensing outcomes, resulting in faster dissemination of university technologies – which is conducive to striving for timeliness. This experience-speed nexus is thus motivated also by the literature on job performance (Bernardin and Beatty, 1984). We hypothesize that more experienced coordinators will complete the transfer process faster, i.e. in a more timely manner.

Hypothesis 1. *More experienced coordinators perform faster.*

We conceptualize performance success by observing *efficiency* levels. Hence, instead of following the more typically used counting of favourable results - often used in technology transfer literature (e.g. Zheng et al., 2013) - we rather turn to efficiency as implied by the job performance literature (Bernardin and Beatty, 1984). The TTOs and the coordinator's goal is to transfer as many technologies 'out the door' (Bozeman et al., 2015), which was also confirmed by our preliminary interviews with TTO staff (see also Supplementary material). The risk of not concluding an agreement or including a low-return agreement is high. Thus, if coordinators wish to increase their potential for higher societal impact (Fini et al., 2018), they will need to increase the number of transferred technologies among their total cases (i.e. increase their efficiency) – which has in turn also the potential to increase the results in terms of dissemination goals (Zheng et al., 2013). At the same time university management is encouraging coordinators to help achieve results that enhance university benchmarking indicators which include more out-the-door results. In time, IP coordinators seek to optimize the potential of their activities and align them with the university's strategic goals. Hence, the more experienced the coordinator, the higher the percentage of transferred patents.

Hypothesis 2. *More experienced coordinators perform more efficiently.*

In order to achieve more impact through higher quality results, opportunity recognition is a key feature in the technology transfer field, otherwise riddled with uncertainties. Although higher experience does not always translate into better quality of results, i.e. better opportunity recognition (Bhagavatula et al., 2010), there is a predominantly positive correlation between them. A good proxy of quality is a *lucrative technology transfer*; defined as a transfer that results in a high revenue. In practice there are only a few very high income-generating licenses (Sterzi and Martínez, 2019), indicating that achieving a highly lucrative license is a complex task, not easily achieved. Experience should help to enhance an IP coordinator's awareness of lucrative transfer opportunities.

Hypothesis 3. *More experienced coordinators perform more lucratively.*

Several types of contextual factors (societal, industry, organization and individual work level factors) are included in Tesluk and Jacobs (1998) experience model. These are all contextual features of the work environment, ranging from macro (e.g. industry) to *meso* (e.g. societal) and micro level (e.g. individual work factors) that are often present in the literature on performance, and mirrored in the literature on multilevel factors influencing technology transfers (e.g. O'Kane et al., 2021). Furthermore, the management literature has recently encouraged more research bridging micro to macro domains, allowing simultaneous addressing of research questions on both levels (Cowen et al., 2022; Crocker and Eckardt, 2014). Multidimensional, even multilevel models including also contextual factors are a potential first step in this direction. Contextual factors play an important part in current theories of performance (e.g., Waldman and Avolio, 1993; Tesluk and Jacobs, 1998), ranging from macro (e.g. societal demographic trends, industry growth) to micro factors.

We *firstly*, take into account the cohort membership as a societal level factor (in line with Tesluk and Jacobs, 1998), based on the same period start of work, thereby following an operationalization thereof in works on cohorts (Carlsson and Karlsson, 1970). Imprinting theory (Simsek et al., 2015) and the newer literature on the boundaries of reflexivity (e.g. Golob and Makarovič, 2019) both enhance the notion that despite differences in individual characteristics, shared individual background matters. *Secondly*, at industry level we take into account the industry growth, which is in line with the Tesluk and Jacobs (1998) model. The industry growth variable also coincides with the macro-level technology transfer factors as pointed out in the multilevel technology transfer literature (e.g. O'Kane et al., 2021; Bolzani et al., 2021; Belitski et al., 2019). *Thirdly*, in terms of the organizational level, we observe the size of the organization or organizational unit (i.e. number of employees) at the focal time, since that also mirrors the pool of experience available. This is also in line with Micozzi et al. (2021) showing that the number of staff at the TTO matters at least for some performance results, as well as with the wider calls for a more holistic picture of understanding the role of human capital (Crocker and Eckardt, 2014). *Lastly*, we identify and conceptualize another level of contextual factors i.e. the object level.

Within this new, object, level we classify the factors relating to material objects and their attributes, i.e. the technology, as well as the immaterial attributes of the object, i.e. the connected immaterial rights and the partners. In this line we take into account the following. In the first category of material technology, we account for the field of technology. In the second category, of immaterial attributes of the object, for licensing we first take into account attributes connected to the *nature of the patent*, as well as we control for the *nature of the partner*, i.e. the licensee. All above are seen as very relevant inside the technology transfer literature (Wu et al., 2015).

3. Research setting, data and methodology

3.1. Research setting

We provide evidence from the Asian science commercialization setting, i.e. that of Japan. Woolgar (2007) highlights that few universities in Japan were engaged in training their administrative or managerial staff. Our preliminary interviews at Japanese TTOs also identified deficiencies in organizational management and lack of specific knowledge as key reasons for sub-optimal performance, which is in line with evidence from other countries (Greenbaum and Scott, 2010; Siegel et al., 2003). Understaffing is also a serious and ongoing issue.

We analysed a licensing and re-assignment database extracted from the administrative records of a well-respected Japanese research university with a long technology transfer tradition. The university exhibits strong patenting and licensing results, according to University Network for Innovation and Technology Transfer's technology transfer survey (UNITT, 2018), being among the top 10 most successful Japanese universities.

Preliminary interviews (see also Supplementary material) showed that the technology transfer staff is engaged in very specialized (*sui generis*) activities, thus diminishing the role of prior experience outside the TTO setting. Also, prior experiences can bring rigidities in the form of schemas, scripts, and cognitions (Gioia and Poole, 1984). These can influence and condition highly skilled workers' assumptions about how the work should be done, which is especially true when these assumptions 'do not fit the new organisational context' (Dokko et al., 2009), for example with coordinators coming from the business sector. Furthermore, these assumptions do not fit the new academic environment and are mismatched with technology transfer goals – as was indicated from our preliminary interviews. Therefore, it is the level of experience at the focal TTO we focus on.

The heavy workload of IP coordinators needs to be acknowledged. They need to prepare suggestions for various technologies for weekly joint meetings and are also tasked with their commercialization. Endogeneity and selection bias may be a problem as well. A significant factor is how cases are assigned: cases are assigned to the next IP coordinator covering the relevant field on the basis of the rotation principle. Although a degree of specialization is common, IP coordinators will usually cover a diverse set of fields, such as Life Science and Nanotechnology, and there is overlap of the fields that an IP coordinator can cover. For example, Nanotechnology was covered by 19 IP coordinators. The primary IP coordinator selected to deal with a certain invention disclosure at that point becomes randomized, and the risk of assigning cases with more potential to more experienced coordinators diminishes.

3.2. Sample description

Unlike many other research endeavours exploring experience, which are based on worker assessment data (Dokko et al., 2009; McDaniel et al., 1988), we use administrative records trying to avoid any subjective biases deriving from supervisors' assessments of work performance. The dataset of the university's patent applications was merged with administrative transfer agreements data as well as human resources data which was provided to us. Our database included 845 licensing cases for the period 2004–2016, managed by 32 coordinators. The patenting data encompassing a longer time span allowed us to account for time lags in licensing as well as to build several of our variables for the passive mode types. There is an increase in the number of licensing activities over time with a spike in licensing activities in 2016. The latter is due to licensing to university start-ups, mirroring licensing in bulk to start-ups.

Within the observed period, the TTO licensed about 9.6% of total patents. In comparison to some of the top US universities, this represents a somewhat lower figure (compare e.g. with Wright et al., 2014). Japanese RU11 universities transfer an estimated 9.1% of all patent applications (UNITT, 2018), confirming that the university selected for this research is indeed very active. 51.6% of coordinators (32 out of 62), who managed to do at least one transfer, on average handled 24 cases of transfers. The most prolific IP Coordinator had 205 transfer cases from 2010 to 2016.

3.3. Methodology

We specified three panel *random effects* regression models (xtreg) using STATA 15 (Allison, 2009; Baetschmann et al., 2015). We assumed correlation over time for a given effect across individuals, thus we constructed a panel data set using a repeated successful licensing measure [1-205] (a proxy for time *t*) for all IP coordinators included in the study [$n = 32$].[1] Panel analysis allowed us to design a model that provided explanation for individual effect (behavior, characteristics) as well as effectiveness over time (more transferred patents).

Table 1 shows three models focusing on a specific facet of successful licensing: speed (*Model 1*, $\mathbf{M_1}$), efficiency (*Model 2*, $\mathbf{M_2}$) and revenue (*Model 3*, $\mathbf{M_3}$). Five measurement modes ($_{\mathbf{MM}}$) of experience are conceptualized as: a) time ($_{\mathbf{MM1}}$), i.e. experience of a coordinator as a time mode (more time at the TTO or more time since first successful transfer event); b) scope ($_{\mathbf{MM2}}$), i.e. more patents assigned, therefore more transfer opportunities, or as more transfer cases concluded, therefore more transfer success; c) type ($_{\mathbf{MM3}}$), i.e. more established connections to individual licensees or principal investigators (PIs) and star PIs; d) density ($_{\mathbf{MM4}}$) which takes into account the workload in a

[1] We believe that the panel analysis is the optimal method to address the issue when dealing with longitudinal data relating to multiple IP coordinators. Consequently, the panel matrix is unbalanced due to the fact that not all IP coordinators are equally successful in licensing.

Table 1
Three models of multidimensional experience and multifaceted performance.

Model	Performance facets (dependent variables)	Experience components and measurement modes (independent variables)
M_1:	Speed (TIMELAPS) =	{*Quantitative components* **Time mode**$_{MM1}$ [[More time at TTO (ExpTime)],
M_2:	Efficiency (CoordEff) =	**Scope mode**$_{MM2}$ [More taken over inventions (CoordPatExp), More cases/events (LicSuccess)]]
M_3:	Revenue (TotIncAmountNew) =	*Qualitative components* **Type mode**$_{MM3}$ [[Previous connections to individual licensees (ExpLicensee_bin), Connections with "star" PIs (NewStarPI), Connection to PIs (ExpPI)]] *Interaction components* **Density mode**$_{MM4}$ [[Heavy Workload (HeavyWorkload), Developmental Punch (DevPunch)], **Timing mode**$_{MM5}$ [Induction period (IndPeriod)]] *Contextual factors* [Cohort (Cohort), Industry growth (IndustryGrowth), TTO Staff (TTOStaff), Structure of tasks (TaskStructure), Field of technology (TField), Granted patent (Granted), Existence of joined patent (JoinPat), Licensing to start-up (Startup), Size of licensee (Size 1)]}

specific time and the intensity of experiences; e) timing ($_{\mathbf{MM5}}$) relates to the period of induction of the IP coordinator. We also control for several types of contextual factors.

In the models, we specified several *dependent variables related to performance*: 1) for speed the licensing time lag (TIMELAPS), 2) for measuring the efficiency facet we consider the coordinator efficiency (CoordEff), and 3) total generated income from technology transfer (TotIncAmountNew) as the revenue facet. Dependent and independent variable descriptions can be found in Table 2 below.

We conducted also several robustness checks, especially as related to *dependent variables*. For licensing time lag (TIMELAPS) the robustness check was done by constructing the time lag between the first time the IP coordinator dealt with an individual underlying technology (not the patent related to it) and time of license. Results hold and the time lag between the first patent-related event and its transfer event time was chosen for the regression, as in essence, the transfer is that of rights (intangibles), and not its tangible underlying technology as such. Next, the coordinator efficiency measure considers all patents handled by a coordinator in comparison to all patents this coordinator transferred in a particular year. Preliminary interviews at TTOs however revealed that coordinators tend to neglect older patents, hence we adapt for this by adopting the time lag of three years for the numbers of relevant patents being handled by a particular coordinator. Furthermore, when using the income variable in our regression, we also considered the fact that coordinators who have been working longer at the TTO may have advantage over newly employed ones, as well as the fact that earlier licensing agreements accrue more licensing income, thus we also conducted the analysis using 'total generated income' (TotInc_bin) and 'coordinator efficiency' (CoordEff_bin) recoded into binary variables. The results hold.

The *explanatory (independent) variables* in the models are tenure at TTO (ExpTime) and time since first license (CooTimLap) reflecting the time mode; assigned patents (CoordPatExp), licensing success, i.e. volume of licensed cases (LicSucces) reflecting the scope mode; connections to individual licensees (ExpLicensee_bin) and connections with PIs (Exp_PI, NewStarPI) reflectine type mode; developmental punch (DevPunch) and heavy workload (HeavyWorkload) reflecting density mode; and induction period reflecting the timing mode. In terms of *time* variables, we include tenure at the TTO, is a *passive type mode*, which is often used in works on experience (Dierdorff and Surface, 2008). However, we originally considered also an *active mode type* for time, indicating active engagement in the environment – time from the first license until the focal agreement (CooTimLap) – but it was later discarded due to high correlation especially with ExpTime and LicSuccess. We also include several contextual factors as control variables in our models reflecting different levels as suggested by Tesluk and Jacobs (1998), whereas we also add object level variables, in particular we control for technology field (TechField) reflecting the material object attribute; and for immaterial attributes of the object we control for granted and joined patents (Granted, JoinPat) reflecting the nature of the patent, i.e. right as well as for attributes of the partner, i.e. licensee, in terms of size and if it is a startup.

4. Results

A quarter of coordinators worked at the TTO for less than a year, especially due to high staff rotation levels in 2013 and later. The average total tenure of IP coordinators was four to six years (4.5 SD). Half IP Coordinators managed to license within the first year at TTO. Social network, i.e. contact between PIs and the IP coordinator, is relatively large with the average size of 30. About half of licensees are from smaller companies or start-ups and about a third are connected to a joint patent. A significant percentage is connected to Nanotechnology. Summary statistics and the correlation matrix are presented in Table 3.

Dependent variable TIMELAPS – used in *the first model* ($\mathbf{M_1}$) – is a measure of transfer speed. The average time lag between the invention disclosure and its licensing was 3.5 years, which is in line with research delineating the average between 2 and 4 years (Heher, 2006). The maximum time of 16.3 years confirms that there are instances where technology is either very embryonic or the licensing organization was slow at realizing its potential. The minimum time, below zero (0), indicates transfer agreements having broader scopes and allowing for inclusion of technologies developed later, i.e. after the initial transfer contract date.[2]

The efficiency of transfer – CoordEff *in the second model* ($\mathbf{M_2}$) – varies across coordinators. The average transferred patent load is approx. 4.0%, adjusting the patent efficiency to 1 if the coordinator transferred more than their current patent load. Four times coordinators transferred more than they acquired during the last three years, as they licensed older patents.

The total income generated from licensing – TotIncAmountNew in *the third model* ($\mathbf{M_3}$) – by individual coordinators also varies significantly, with most coordinators generating less than 5% of the income across the whole period. Nonetheless, the maximum is reached by a coordinator generating 28.2% of the total income.

Three panel regression models are used to explore the relationships between experience and three facets of (licensing) performance, i.e. speed ($\mathbf{M_1}$), efficiency ($\mathbf{M_2}$) and generated revenue ($\mathbf{M_3}$), on the level of individual IP coordinators. The models include several variables reflecting the three types of components (quantitative, qualitative and interaction), and within them the five measurement modes (time and scope, type, density and timing), as well as contextual factors as control variables. Table 4 provides the results of the three models.

[2] This confirms the previous suggestions that the inclusion of new technologies in a pre-existing licensing agreement is a relatively widespread phenomenon across TTOs. Nonetheless, we only detect approx. 2% of such cases in our entire licensing sample.

Table 2
Variable descriptions.

Facet	Component	Variable acronym	Variable name	Mode type	Description*
		Dependent variables			
Speed		TIMELAPS	Licensing speed		TIMELAPS is the time lag between invention disclosure and the date of license (calculated in days).
Efficiency		CoordEff	Licensing efficiency		The measure considers all taken over patents by each IP coordinator over the last three years and all transferred patents over the year in question (by the same coordinator).
Revenue		TotIncAmountNew	Licensing revenue		Total generated income from the license.
Mode		**Independent variables**			
Time	Quantitative	ExpTime	Tenure at TTO	P	Time between when IP coordinator started working at the TTO and this agreement (calculated in days).
Scope	Quantitative	CoordPatExp	Assigned patents	P	Number of patents assigned to a particular IP Coordinator until that point.
Scope	Quantitative	LicSuccess	Licensing Success	A	Number of licensed patents by IP Coordinator until that point.
Type	Qualitative	Exp_Licensee_bin	Licensee network	A	Binary variable measuring prior experience with this particular licensee, i.e. organization that has licensed a certain technology. Binary variable (1=yes, 0=no).
Type	Qualitative	NewStarPI	Network with star PIs	A	Connections between IP coordinators and principal investigators (PI) that are considered "star" PIs in terms of high propensity to license (3 or more licenses =1, else=0). We discover 30% of star PIs.
Type	Qualitative	ExpPI	Network with PIs	P	Number of connections between IP Coordinator and unique principle investigators (PIs) until that point.
Density	Interaction	HeavyWorkload	Heavy Workload	P	Binary variable for workload growth per coordinator within a timeframe. If workload increased more than 100% from previous time then we have recorded heavy workload (1=yes, 0=no).
Density	Interaction	DevPunch	Developmental Punch	A	Binary variable based on the licensing density, which is set to 1 for observations for years in which the coordinator operated, and in which the density of the licensed cases has been high (top 25% of all cases=1, else=0).
Timing	Interaction	IndPeriod	Induction Period	P	Induction period is defined as time between their employment and officially being assigned the first case (in days), mirroring how much input a focal IP Coordinator was able to get until that time.
		Contextual factors			
Societal level		Cohort	Cohort membership		Based on start of their tenure at the TTO, the coordinators were allocated into three distinct cohorts (Cohort 1 starting in 1997, Cohort 2 starting in 2004, Cohort 3 starting in 2011). Cut off points were based on major changes in the organizational structure or the TTO environment.
Industry level		IndustryGrowth	Industry Growth		Based on survey data from University Network for Innovation and Technology Transfer (UNITT) on licensing and patenting results of Japanese universities, we compute the number of patents normalized by number of invention disclosures (2004 to 2016).
Organizational level		TTOStaff	TTO staff		Number of staff working at the TTO in a certain year.
Ind. work environ.		TaskStructure	Structure of tasks		The relationship between the number of patenting cases and the number of licensing cases assigned to the focal IP coordinator.
Object level		Tfield	Technology field		Field of technology is a dummy variable. Nanotechnology as a commonly licensed technology is 1.
Object level		Granted	Granted patent		Binary variable if patent was granted (granted=1)
Object level		JoinPat	Joint Patent		Binary variable indicates if the patent has been jointly patented (joint patent =1)
Object level		Startup	Startup Licensee		Being a focal university's start up (yes=1).
Object level		Size	Licensee Size		Binary variable for the size of licensee. Since there are many small sized licensees the value 1 is a small company.

**All variables are based on administrative data (except if indicated otherwise).*

*All variables are based on administrative data (except if indicated otherwise).

Time, type and timing are relevant for achieving results in terms of speed. The most impactful explanatory variable of speed is the number of connections between IP Coordinator and unique principal investigators (PIs) – *ExpPI*. There is a full spectrum of components (quantitative, qualitative and interaction) affecting speed. Similarly, can be said for efficiency, with quantitative and interaction components featuring especially prominently. Revenue on the other hand is solely affected by density and timing, i.e. the interaction components.

In the first model ($\mathbf{M_1}$) the time measurement mode had a positive statistically significant impact on the speed of transfer, same as within the scope mode, the licensing success, while the effect of assigned cases is not significant. Neither longer tenure at TTO nor more experience in terms of successful licenses increase the speed of licensing. On the other hand, type measurement modes denoting the complex networking (licensee network, network with PIs and with star PIs) help increase the speed of transfer. Similarly, also timing (induction period) contributes to the increase of transfer speed. Several contextual factors have a statistically significant effect on the speed of transfer. Industry growth is the most important in shortening the time to transfer. A company being a startup also helps in shortening the time to transfer, while cohorts, task structure and granted might slow down the process of transfer. *We only find support for our hypothesis 1 when taking into consideration the type and timing measurement modes.*

The time mode, i.e. tenure at the TTO, has a positive statistically significant impact on the efficiency measure ($\mathbf{M_2}$). Within the scope mode, only one variable has a statistically significant effect on the

Table 3
Descriptive statistics and correlations.

	Descriptives statistics					Correlation coefficients									
	Mean	SD	n	Min	Max	TIMELAPS	CoordEff	TotIncAmountNew	ExpTime	CoordPatExp	LicSuccess	ExpLicensee_bin	ExpPI	NewStarPI	JoinPat
TIMELAPS	1273.40	1069.26	839	-357	5975	1									
CoordEff	0.44	0.98	841	0	4	0.518	1								
TotIncAmountNew			845			0.160	0.219	1							
ExpTime	2164.45	1198.26	845	14	7275	0.378	0.514	0.200	1						
CoordPatExp	349.97	264.28	841	2	1197	-0.214	-0.472	-0.034	-0.492	1					
LicSuccess	10.13	7.90	845	1	33	0.285	0.162	-0.141	0.397	0.004	1				
ExpLicensee_bin	0.42	0.49	845	0	1	0.197	0.355	0.416	0.492	-0.121	0.040	1			
ExpPI	30.12	26.74	845	0	131	-0.161	0.053	-0.263	0.328	-0.162	0.515	-0.297	1		
NewStarPI	0.52	0.50	845	0	1	-0.140	-0.312	0.132	-0.075	0.366	-0.045	0.284	-0.370	1	
JoinPat	0.33	0.47	845	0	1	-0.213	-0.265	-0.399	-0.344	0.005	0.065	-0.407	0.109	-0.121	1
Granted	0.43	0.50	845	0	1	0.492	0.280	-0.014	0.129	-0.088	0.117	-0.122	0.014	-0.205	-0.059
Startup	0.33	0.47	845	0	1	-0.140	-0.250	0.336	-0.001	0.348	-0.162	0.459	-0.403	0.546	-0.412
Size	0.52	0.50	826	0	1	-0.124	-0.299	0.159	0.168	0.289	0.164	0.371	-0.102	0.509	-0.321
TField	0.33	0.47	845	0	1	-0.211	-0.243	0.235	-0.060	0.230	-0.252	0.360	-0.365	0.468	-0.072
TTO_staff	18.19	3.70	845	11	22	0.050	0.161	-0.314	-0.106	-0.283	0.036	-0.623	0.377	-0.387	0.243
Cohort	1.78	0.74	845	1	3	-0.245	-0.397	-0.109	-0.704	**0.687**	-0.020	-0.116	-0.317	0.304	0.217
HeavyWorkload	0.30	0.46	845	0	1	0.054	0.404	0.416	0.254	-0.077	-0.061	0.360	-0.019	0.052	-0.310
IndPeriod	19.07	41.21	845	0	558	-0.185	-0.079	0.002	0.075	-0.038	-0.207	0.036	-0.129	0.029	0.056
DevPunch	0.57	0.50	845	0	1	0.198	0.215	0.196	-0.110	0.181	-0.059	0.054	-0.262	-0.112	-0.152
TaskStructure	0.17	0.12	845	0	1	0.110	0.262	0.491	0.366	-0.200	-0.274	**0.621**	-0.388	0.279	-0.493
IndustryGrowth	0.95	0.17	840	0	1	-0.524	-0.507	-0.019	-0.218	0.496	-0.031	0.146	0.001	0.379	0.050

	Correlation coefficients (cont.)										
	Granted	Startup	Size	TField	TTO_staff	Cohort	HeavyWorkload	IndPeriod	DevPunch	TaskStructure	IndustryGrowth
TIMELAPS											
CoordEff											
TotIncAmountNew											
ExpTime											
CoordPatExp											
LicSuccess											
ExpLicensee_bin											
ExpPI											
NewStarPI											
JoinPat											
Granted	1										
Startup	-0.161	1									
Size	-0.173	**0.687**	1								
TField	-0.177	0.521	0.402	1							
TTO_staff	0.247	-0.576	-0.500	-0.511	1						
Cohort	-0.230	0.180	0.125	0.185	-0.267	1					
HeavyWorkload	-0.062	0.198	0.064	0.111	-0.107	-0.141	1				
IndPeriod	-0.139	0.104	0.071	0.106	-0.180	-0.042	-0.015	1			
DevPunch	0.105	0.065	-0.064	-0.010	-0.102	0.085	0.087	-0.061	1		
TaskStructure	-0.092	0.504	0.299	0.423	-0.382	-0.317	0.296	0.296	0.046	1	
IndustryGrowth	-0.380	0.357	0.402	0.390	-0.491	0.490	-0.016	0.110	-0.056	-0.060	1

Note. Correlation coefficients above 0.6 in **bold**. Income amounts are omitted to preserve confidentiality.

Note. Correlation coefficients above 0.6 in **bold**. Income amounts are omitted to preserve confidentiality.

dependent variable. In contrast, higher number of assigned cases affects coordinator efficiency negatively. Observing the type measurement mode, licensee network has a positive effect on efficiency, while network with star PIs is the opposite. Several contextual factors are important in explaining efficiency. A positive effect can be observed for cohort membership, number of TTO staff, task structure and number of granted patents. Industry growth, nanotechnology field, jointly patented patents, university startups, small size licensees, on the other hand affect coordinator efficiency negatively. *Hypothesis 2 is partially supported.*

Model (3) focuses on revenue as a dependent variable in the model. Time, scope, type or timing do not have a statistically significant effect on income; only interaction components (heavy workload and developmental punch) have a positive impact on the income. Same is true for only a few contextual factors. Joint patent, licensee size and number of staff working at the TTO in a certain year have a negative statistically significant effect on the revenue, while task structure has a positive effect. *Hypothesis 3 is not supported.*

5. Discussion with implications

5.1. Theoretical and methodological implications

In line with prior literature (Quinones et al., 1995; Tesluk and Jacobs, 1998), our findings suggest that experience is generally affecting performance. However, within the still vivid debate (Micozzi et al., 2021) over a generally existing positive effects of more experience on performance - where only the magnitude of the relationship is up for debate (Unger et al., 2011) - our results more firmly support the stance that there are types of experiences which do not affect, or even impede, performance (Avery et al., 2003; Baron and Henry, 2010; Donegan et al., 2019; Nass, 1994; North, 2019). We discover that the conceptualization and operationalization of experience may affect the results, including the direction of the effects, and interpretations regarding the interplay of experience and performance.

We thus posit that the experience needs to be conceptualized as a multidimensional construct preferably accounting for quantitative components, qualitative components, and interaction components. We contribute to further construct clarity of multidimensional experience inside the science commercialization field by explicating the type measurement mode of experience as the networking experience, since due to the brokering nature of IP Coordinators' work, mastering the complexity of the social network and the ability to connect distal science commercialization actors, is key for IP coordinators. A similar operationalization could be utilized when exploring other highly skilled individuals who act as brokers, thus sharing some similarities with the present setting (Tesluk and Jacobs, 1998).

Passive and active mode types were added as an additional layer to the multidimensional model to account for strength of experience. For e.g. should we follow the logic of learning by doing as encompassing only activities with desired results (Reese, 2011), then we would refer to the active mode type. But if we take into account also trial-and-error learning (Reese, 2011), which in the case of IP Coordinators entails accounting for all patenting cases assigned to them, we would be referring to the passive mode type. This also follows recent debates on the value of learning from failures in TTO settings (Zheng et al., 2013). Extending the Tesluk and Jacobs (1998) model of contextual factors, we also add *object level factors*. These include technology as material objects, as well as rights and partner attributes as immaterial objects. For more general use we point out that their operationalizations can be context dependent – similarly as it is true for other elements of multidimensional experience models (see e.g. Tesluk and Jacobs (1998) on the qualitative components). Our results indicate that the object level contextual factors need to be taken into consideration when exploring the experience-performance nexus.

Our multidimensional experience approach allows us to understand more nuances in regard to internal factors of science commercialization

Table 4
Panel estimation models.

Components	Measurement modes	Performance facets		
		Speed [TIMELAPS] (M_1)	Efficiency [CoordEff] (M_2)	Revenue [TotIncAmountNew] (M_3)
EXPERIENCE				
Quantitative	Time			
	Tenure at TTO [ExpTime]	0.512*** (0.059)	0.000***(0.000)	0.004 (0.005)
	Scope			
	Assigned patents [CoordPatExp]	−0.262 (0.190)	−0.000***(0.000)	−0.004 (0.013)
	Licensing Success [LicSuccess]	37.179*** (7.191)	0.001 (0.004)	−0.208 (0.461)
Qualitative	Type			
	Licensee network [ExpLicensee_bin]	−142.486*(79.486)	0.624***(0.070)	−10.307 (8.631)
	Network with star PIs [NewStarPI]	−163.646***(56.307)	−0.158***(0.050)	−4.931 (6.156)
	Network with PIs [ExpPI]	−19.538***(1.484)	0.002 (0.001)	−0.162 (0.152)
Interaction	Density			
	Developmental Punch [DevPunch]	102.630**(45.991)	0.392***(0.041)	15.702***(4.986)
	Heavy Workload [HeavyWorkload]	−41.599 (47.384)	0.480***(0.043)	44.782***(5.293)
	Timing			
	Induction Period [IndPeriod]	−4.19491***(1.307)	−0.001 (0.000)	−0.248***(0.071)
CONTEXTUAL FACTORS				
Societal level	Cohort membership [Cohort]	729.635***(128.060)	0.561***(0.057)	4.578 (6.908)
Industry level	Industry Growth [IndustryGrowth]	−2418.203***(224.860)	−1.352***(0.168)	−14.035 (20.424)
Organizational level	TTO staff [TTO_staff]	−4.278 (12.171)	0.050***(0.008)	−3.726***(1.010)
Individual work environment	Structure of tasks [TaskStructure]	1296.922* (732.698)	1.480***(0.271)	206.500***(33.074)
Object level	Technology field [TField]	58.079 (62.916)	−0.128**(0.053)	0.489 (6.433)
	Granted patent [Granted]	338.718***(46.987)	0.261***(0.041)	3.454 (5.044)
	Joint Patent [JoinPat]	−89.801 (62.263)	−0.139***(0.052)	−16.088**(6.395)
	Startup Licensee [Startup]	−204.613**(84.581)	−0.321***(0.068)	7.998 (8.335)
	Licensee Size [Size]	−3.328 (66.156)	−0.354***(0.057)	−8.112 (6.967)
	Constant	*1439.911***(424.188)*	*−1.286***(0.292)*	*79.000**(35.646)*
	Obs.	*813*	*817*	*817*
	Groups	*32*	*32*	*32*
	Adj R squared	*0.5677*	*0.7481*	*0.388*
	Wald $\chi2(18)$	*1314.29****	*2370.51****	*505.95****

Notes. Coefficients (standard errors). Random-effects regression coefficients (xtreg - panel regression model). Significance level: at the 1%***, 5%** and 10%* levels.

and their effects. The multidimensional experience can either be accounted for on an individual level or as a composite construct. To explore the multidimensional experience with the multi-faceted performance outcomes, we rely on individual effects. By including human resource records (especially case assignment data) we were able to overcome the limitations of administrative data showing the first or last (or current) individual in charge of a case. This allowed us a precise exploration of experience levels of individuals, and enabled us to add to the science commercialization literature showing that TTO staff could benefit from at least some type of experiences (see e.g. Kloke and Krueken, 2010; Siegel et al., 2004; Zheng et al., 2013). Our individual level focus also revealed some additional intricacies of the TT process as elaborated below.

5.2. Speed and efficiency implications

> *"We try to get as many technologies out the door, as fast as we can, to create opportunities."*
>
> TTO director's interview extract

In general, more experienced IP coordinators should license faster and more efficiently. However, our research shows that time to license can lengthen, although certain types of experiences increase. This is true for tenure at the TTO (passive mode type) and licensing success (active mode type), as well as for developmental punch (active mode type).

In terms of tenure, the *burnout effect* (Mann, 2013) may cause a gradual slow-down in the speed of work. Furthermore, negotiation skills should come with a longer tenure at the TTO which can have as a consequence with a more refined ability to identify and close a good and fair deal, but this might come at the expense of licensing speed. Yet, this explanation seems less likely, since experience in terms of tenure is related to higher efficiency, but not to more revenue. In terms of IP coordinators who often experienced periods of high density of licensing cases, i.e. activities with (positive) results, they do achieve better results in terms of efficiency, but not also their speed of licensing. In these cases efficiency seems to be achieved on account of losing speed. Our research confirms that speed increases with higher availability of network ties as conduits (Owen-Smith and Powell, 2003, 2004; Bercovitz et al., 2019), i.e. in terms of increased networking experience, and having sufficient training prior to engaging with initial cases. Approaching star PIs is a useful strategy if speed of licensing is important, though the impact on effectiveness is questionable.

Nonetheless, more experience with licensees does increase efficiency. There is a discrepancy between the two passive mode types (high level of assigned cases, heavy workload) influencing efficiency. Simply assigning more and more cases to a particular IP coordinator will not improve their efficiency, but probably overburden them with stagnant assigned cases. On the other hand, heavy workloads seem to have a more positive impact probably due to only limited periods of challenging work demands (Wu et al., 2019). This also indicates the absence of the Matthew effect (Merton, 1968), which would suggest that more experienced IP coordinators are assigned cases with more potential. Object level contextual factors matter most for efficiency, and less for speed (granted patents and startup) and revenue (joint patents).

Contrary to the previous literature, which predicted that qualitative components could hold more explanatory power (e.g. Tesluk and Jacobs, 1998), our results do not support this notion, but are more in line with Van Iddekinge et al. (2019), who also did not find significant difference between exploratory power of quantitative and qualitative prehire experiences. Since Van Iddekinge et al. (2019) found only weak support for their result, and their conclusions were limited to pre-hire experience, our research reinforces the ideas that neither quantitative and qualitative are dominant, and provide evidence that this is true also in other contexts and frames (i.e. beyond pre-hire experience). In contrast to our expectations, the same is also true for the division between active and passive components. Seemingly, the strength of experience does not contribute to the explanatory value of the model.

When developing a TTO human resource strategy the following should be considered. Coordinators employed for a longer period or those who are more successful at finalising deals are not necessarily focused on performing quickly. An interesting implication arising from our work is that more experience in terms of scope may not exhibit neither efficiency nor speed gains, thus the managers need to adopt a wider understanding of who is they deem as experienced.

IP coordinators with larger researcher networks will be more likely to license in a shorter period of time. To achieve efficiency, TTO managers should consider giving more opportunities to coordinators with previous connections with licensees and strive to nurture ties with actors from previous successful deals. Events, platforms or other opportunities for interaction between IP coordinators and other actors should be provided. In terms of individual versus group effects, we can see that TTO size can have a positive impact on the effectiveness of transfer of patents, yet there are no gains in terms of decreased time. Our results are thus also in line with the results of Micozzi et al. (2021) on increasing returns of more staff at the TTO in terms of scope, but whereas they find non-significant effect on licensing revenues, we however observe diminishing returns in terms of revenue. Hence, neither works showcases any significant returns of increasing the number of staff at TTO for revenue. Similarly, cohort membership also increases efficiency. More IP coordinators at the TTO can more easily manage the flow of incoming disclosures, while pushing patents, and focus on licensing. This implies there is a benefit to be gained in setting up opportunities to share knowledge between IP coordinators. This knowledge-sharing opportunity can be in the form of (weekly) meetings where cases are reported to all colleagues, who can either utilize that knowledge for their own cases or may be able to provide additional suggestions and feedback on how to proceed (e.g. information on potential licensees etc.). Good practice can also be shared periodically. For example, there are instances of TTOs hosting innovation and creation contests on an annual basis with the goal of showcasing the excellent transfer cases occurring within that year and to serve as a platform facilitating suggestions for improvements to the process at the TTO.

5.3. Revenue implications

"Technology Transfer – a Miserable Business Model."

Stevens (2017)

There is a lack of a significant effect of experience on revenue, with the exception of the interaction components factors. The lack of effect of quantitative and qualitative components of experience can have different explanations.

Firstly, when the result is dependent on third-party involvement, the effect of experience of the internal staff naturally competes with that of the external actors. In the case of university licensing, albeit the IP coordinators play a key role in the process, there are other actors with strong interests involved; the PI with interest in having a technology that has been transferred to the licensee, and the licensees which would commonly seek favourable pricing for the licenses. This is in line with the indications by Radaelli et al. (2018) about the 'softened' effects of experience due to external conditions.

Secondly, experience generates scripts or schemas that can be re-applied (Gioia and Poole, 1984), however licensing is a non-routinized activity with high risks demanding flexibility – rendering these already known practises and tactics useless for re-application, and we can rather be faced with an 'experience trap' (Hahn and Kim, 2021). Schemas developed in one context can facilitate performance in that context, leading to simplifying, particularly more routine and repeated tasks. Specifically, achieving a lucrative license often means that new tactics need to be applied (more so than when just trying to license or license fast), hence more context-specific prior scripts and schemas might not make a difference in subsequent cases. This is in line with indications on the relatively poor returns in terms of pre-hire experience (Van Iddekinge et al., 2019), and confirms results from studying another profile of highly skilled experts, that of patent examiners, for which Cockburn et al. (2002) discover that, when it comes to conducting cases with better outcomes (and not just more cases), experience in terms of time and scope do not really matter.

Thirdly, in our research setting, reasons connected specifically to the researched area of science commercialization, with skewness in revenue performance, and with rare big winners can be at play. Our data does show that there is a non-negligible number of licenses not even compensating all patent costs, which means more experience is not necessary reflected in garnered licensing revenue.

Conventional wisdom indicates that potentially high earning transfers should be dependent on the experienced IP coordinators to match the technology with appropriate industry partners. In contrast, we discover that only the interaction component plays an important role in revenue generation. The density of activities impacts revenue generation positively, which is not true for longer induction periods. Training does not impact revenue generation in every case. Our results confirm the claims of Bhagavatula et al. (2010), that better opportunity recognition does not always arise from increased experience levels.

Within contextual factors only task structure seems to matter for increasing revenue. Task structure is also the only contextual factor which is significant across all three models. This indicates that managers should ensure the *ex ante* balance between assigning patenting cases with more or with less potential to the individual IP Coordinators, as well as the *ex post* balance between the total assigned cases and those that the IP coordinators manage to license. The latter suggests the need to set up appropriate monitoring mechanisms.

5.4. Limitations and future research

Although our model includes contextual factors on various levels, literature on experience – i.e. Tesluk and Jacob's model – also includes individual difference factors. Our density component factors can only provide some limited explanations, for example since heavy workload at particular times may induce stress, we could infer some conclusions related to the levels of stress as an individual difference factor. Literature on job performance, on the other hand, indicates the importance of some other factors such as interpersonal contact or need for supervision. However, our data does not allow us to provide further related insights such as those related to motivation, aptitude, satisfaction, and supervision. Furthermore, the literature on experience also points to several levels of experience specification, including work group level. Accrued experience at the meso-level might provide complementary insights as also pointed out in the literature on technology transfer (O'Kane et al., 2021) and supported by theories on cultural capital (Bourdieu, 2018). Opportunities can also arise from cross-boundary research (Cowen et al., 2022), in terms of conjointly taking into account various levels.

In this paper we focused on quantitative aspects of performance, however we believe that further research taking into account also more qualitative aspects such as prestige, legitimacy, reputation and prestige (O'Kane et al., 2015; Shen et al., 2022) can contribute to a more holistic view. Such a qualitative aspect approach would be especially valuable when conducting a comparative analysis or a multiple case study. Job performance literature also reminds us of the importance of loyalty and low turn around rates since these also translate into higher organizational performance. In this line it is possible to observe rotation rates of staff at the TTO if we also have access to human resource data.

Our measurements of experience are focused on experience gained during tenure at the focal organization. We do not include any pre-hire experience (Radaelli et al., 2018; Van Iddekinge et al., 2019), since our data preclude us from doing so. It would be beneficial to further test the presumption that context-specific scripts and schemas might not make a difference for handing highly heterogeneous licensing case attributes.

Lastly, several biases need to be addressed. There might be selection bias, where the more experienced highly skilled staff are assigned cases with higher potential. We controlled for this by choosing an organizational setup where case assignments are randomized. Furthermore, data on performance might be prone to subjective assessments (Dokko et al., 2009) as it is often provided by highly-skilled individuals or their supervisors. We avoided this bias by deriving our implications from administrative datasets. We were also able to merge individual invention, patent and licensing data as well as to connect this data to the human resource data, taking into consideration the dynamic approach of (re-)assignments, and thus avoid the use of static administrative data influencing the results.

6. Conclusion

Managers have long been advised to use well-designed strategic plans to control the innovation process, yet this requires understanding of the underlying mechanisms. The individual level exploration of experience-related factors allows us to witness the interplay between multidimensional experience and multifaceted performance outcomes of individual highly skilled administrative staff in brokering positions. Furthermore, the individual approach allows the identification of bottlenecks and intricacies of the observed process.

We provide a model accounting for experience and performance. We refine and extend the Quinones et al. (1995) and Tesluk and Jacobs (1998) models. *Firstly*, we add the mode type layer, accounting for the strength of experience. *Secondly*, we conceptualize the type measurement mode as connected to the network, since the essence of working as brokers entails managing social complexities. *Thirdly*, we extend the array of contextual factors to include also object level contextual factors, which we believe to be of particular importance when analysing the experience of highly-skilled individuals.

This paper contributes to enhancing the understanding of multidimensional experience factors that influence successful performance in multi-goal-oriented setups, such as that of science commercialization. We show that diverse conceptualizations and operationalizations of experience can lead to diverse interpretations regarding its effects on performance. More specifically, this study explores the importance of individual IP coordinators' experience and the effect on commercialization results – an often-forgotten piece of the puzzle if we want to untangle the science commercialization processes and the role of science commercialization brokers.

While we find limited support for our first two hypotheses of the effect of experience on speed and efficiency performance, we also observe that there are facets of performance that remain almost unaffected by increased experience levels of the highly skilled staff at TTOs. This is true for the revenue generation, since only interaction components seem to play an important role (and only density has a positive effect).

The article provides insights into how multi-goal-oriented organizations with highly-skilled administrative staff, TTOs in particular, can benefit from more evidence-based organizational and human resource strategy. Experience in general matters, but we show that the recommendations depend mainly on prioritized goals of organizations. Recent works still point to data deficits concerning human resource data (O'Clery and Kinsella, 2022), also as a limitation to related policy-making. This is also limiting our understanding of mechanisms at play. We illuminate in greater detail than was previously available the experience-performance nexus, and show that experienced IP Coordinators may influence the licensing in unexpected ways, hence studying how increased experience of IP Coordinators influences the different facets of licensing performance and allows us to have a more nuanced understanding of the effects of experience in multi-goal organizations.

External validity is however often a limitation of case studies, as it only allows for analytical generalization (Yin, 1994). Our case study provides a deep understanding of the technology transfer characteristics based on compiling the licensing dataset enriched with further patenting and human resource data. The focal case study is a typical successful TTO, where processes related to technology transfer are not inherently specific - thus allowing for a degree of generalization. Furthermore, universities and TTOs share many characteristics across and within countries such as issues permeating the involved individuals (e.g., lack of training, issues with knowledge etc.), processes (e.g. the learning on the job) and same-type objects involved (evolving around highly innovative technologies) (Fini et al., 2018). The phenomena as observed within our case study (e.g. the processes, the attributes of involved actors etc.) correspond well with what we know from theory. A study with clear rationale for the case selection, including details on the study context (Cook and Campbell, 1979; Coviello and Jones, 2004) and additional qualitative preliminary interviews (see Supplementary material) enables us to gain substantial insights in understanding our setting as well as to reconcile the results with the theory. The weak point remains our inability to account for potential heterogeneity in terms of the comparison between different organizations, although we did perform several robustness checks (reminiscent of the nested approach) which indicated that the observed relationships are stable across the sample and in time (with technology transfer literature often citing the lack of insights from longitudinal data as limitations (e.g. Muscio, 2010)). For cross validation purposes, we appeal for more university-level research to be conducted in order to discern further TTO environments.

Nonetheless, the processes with similar characteristics as the ones we describe could be generalizable to other settings with highly skilled individuals performing high-complexity jobs, but which are operating within frameworks of limited choices (Cardozo et al., 2011). We use IP coordinators as a model of highly skilled administrative staff, but encourage other profiles to be studied. These can also confirm whether the findings, derived from the science commercialization context, in relation to the role of experience of highly skilled individuals, can inform wider management, human resource and organizational theory to a larger degree.

CRediT authorship contribution statement

Term	Definition	Contribution
Conceptualization	Ideas; formulation or evolution of overarching research goals and aims	DM, JS
Methodology	Development or design of methodology; creation of models	DM, JS
Validation	Verification, whether as a part of the activity or separate, of the overall replication/reproducibility of results/ experiments and other research outputs	JS
Formal analysis	Application of statistical, mathematical, computational, or other formal techniques to analyze or synthesize study data	DM, JS
Investigation	Conducting a research and investigation process, specifically performing the experiments, or data/evidence collection	DM
Resources	Provision of study materials, reagents, materials, patients, laboratory samples, animals, instrumentation, computing resources, or other analysis tools	DM
Data Curation	Management activities to annotate (produce metadata), scrub data and maintain research data (including software code, where it is necessary for interpreting the data itself) for initial use and later reuse	DM, JS
Writing - Original Draft	Preparation, creation and/or presentation of the published work, specifically writing	DM, JS

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	the initial draft (including substantive translation)	
Writing - Review & Editing	Preparation, creation and/or presentation of the published work by those from the original research group, specifically critical review, commentary or revision – including pre-or postpublication stages	DM, JS
Visualization	Preparation, creation and/or presentation of the published work, specifically visualization/data presentation	DM, JS
Project administration	Management and coordination responsibility for the research activity planning and execution	DM
Funding acquisition	Acquisition of the financial support for the project leading to this publication	DM

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Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

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Appendix A. Supplementary data

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