

Maly, Leonard Omer; Avinadav, Tal

Article

Smart allocation of a developer's spending on product quality and non-salary employee benefits in a supply chain of apps

Operations Research Perspectives

Provided in Cooperation with:

Elsevier

Suggested Citation: Maly, Leonard Omer; Avinadav, Tal (2025) : Smart allocation of a developer's spending on product quality and non-salary employee benefits in a supply chain of apps, Operations Research Perspectives, ISSN 2214-7160, Elsevier, Amsterdam, Vol. 14, pp. 1-15, <https://doi.org/10.1016/j.orp.2024.100320>

This Version is available at:

<https://hdl.handle.net/10419/325800>

Standard-Nutzungsbedingungen:

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

Terms of use:

Documents in EconStor may be saved and copied for your personal and scholarly purposes.

You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.

If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.



<https://creativecommons.org/licenses/by-nc/4.0/>



Smart allocation of a developer's spending on product quality and non-salary employee benefits in a supply chain of apps

Leonard Omer Maly^{*} , Tal Avinadav

Department of Management, Bar-Ilan University, Ramat Gan 5290002, Israel

ARTICLE INFO

Keywords:

Supply chain management
Revenue sharing
Quality
Non-salary benefits

ABSTRACT

Qualified and capable employees are crucial for the success of high-tech companies. With an ever-shrinking pool of talent, employers are forced to devise creative recruitment and retention methods, which increasingly take the form of heavy spending on non-salary benefits. The present study contributes to the existing supply-chain literature through examining the role played by such benefits in a two-agent system consisting of a platform and an app developer. In particular, we examine the effect of non-salary benefits on the outgoing quality created by the employees of the app developer. The parties follow a Stackelberg sequential game led by the platform to accurately reflect the interaction in the market, allowing us to reach equilibrium using backward induction. Our results indicate that when app developers are more risk averse or face greater uncertainty, they spend a greater amount on non-salary benefits and comparatively less on app quality. This finding highlights the importance of investing in workers, particularly in uncertain times. We further extend the applicability and robustness of our findings by introducing multiple developers to our two-agent system. The extension proves that the platform charges a universal commission rate, irrespective of the number of developers – a finding that is consistent with current practice. Given the non-linear effect of key model parameters on the profits of the supply-chain members in both the single and the multiple-developer setups, we also utilize numerical analyses and arrive at telling managerial implications for all parties.

1. Introduction

While base salaries continue to play a fundamental role in attracting capable employees to workplaces [15], recently, non-salary benefits and “perks” seem to have taken center stage. High-tech and innovation-based companies regularly publicize their offerings, including leisure and relaxation facilities, quality catering and onsite wellness activities [7]. For example, Israeli high-tech firms organize extravagant parties and all-inclusive vacations to the Caribbean. Some tech workers reportedly approach recruiters in anticipation of a set standard of such benefits when joining a company, suggesting their capacity to facilitate recruitment efforts [17]. This strategy corresponds to the ever-growing shortage of tech professionals [8], encouraging high-tech firms to diversify their spending on non-salary benefits and set themselves apart from the rest.

Firms that develop mobile and computer apps (hereafter “apps”) seem to have adopted this approach as high-tech ventures. Tinder, for

example, offers its employees legal assistance, paid vacations, and training mentorship, among other benefits.¹ Although revenue from digital apps was projected to reach \$430B in 2022 within the mobile sector alone (with an average annual growth of approximately 10 %),² as mentioned, the pool of talent within the tech industry remains limited. Therefore, it could be worthwhile offering non-salary benefits in order to attract quality employees, although caution needs to be exercised when using such a strategy given the uncertain nature of the effect of such perks on employee performance [17].

Due to the special features of apps as virtual products [10], an app development firm primarily incurs costs related to the quality of the product. More specifically, spending on elements such as visual design, functionality, reliability, and security usually raises the quality of the app, which is essential for its competitive positioning [1]. Since human developers can exercise a substantial influence on app quality (for empirical evidence of the phenomenon for software developers, see [16]), in addition to the aforementioned quality-inducing elements, this

^{*} Corresponding author.

E-mail address: leo.o.maly@gmail.com (L.O. Maly).

¹ https://www.glassdoor.com/Benefits/Tinder-US-Benefits-EI_IE916118.0,6_IL.7,9_IN1.htm.

² <https://www.statista.com/outlook/dmo/app/worldwide>.

study considers the effect of non-salary benefits on app-quality achievement.

Developers of mobile apps commonly reach their end customers by offering the app via a distribution platform (hereafter, “platform”). The biggest platforms are Apple’s App Store and Google Play (together accounting for 95 % of the market outside China³). With millions of apps on each of these platforms, both offer a universal contract to app developers, which stipulates that the platform will keep a defined percentage of the revenue generated by the app (15–30 %). The platform facilitates the distribution efforts and billing process, while the developers maintain ownership of their apps.⁴ Therefore, the interaction between the two parties resembles a consignment contract with revenue sharing [1].

This study models the business interaction as a two-agent system consisting of a platform (“it”) and a developer (“he/she”). Using a game-theoretic approach, we construct the following Stackelberg game led by the platform: First, the platform sets the contract term, i.e., the percentage of the product’s revenue that it charges as commission. Second, the developer makes two decisions simultaneously – his/her intended level of app quality and the amount spent on non-salary benefits for his/her employees. The game’s nature reflects the interaction in the app market, as developers follow the platform’s existing terms when launching their app on it (as in [2,4]). As suggested by previous studies [1,2,10], we only consider the cost of quality incurred by the developer; the platform is assumed to have negligible marginal costs. This assumption aligns with the characteristics of apps as digital products since their inception over a decade ago [9], allowing platforms to timelessly-distribute millions of apps⁵ with ample capacity to fulfill demand. Since we assume that non-salary benefits have an effect on app quality – but one that is uncertain in nature – we consider the developer’s attitude towards risk in his/her objective function.

We focus on non-salary benefits in the form of initiatives (such as onsite activities, parties, and trips) rather than common per-employee benefits (such as insurance or retirement benefits). Our reasoning is twofold. First, common per-employee benefits tend to be agreed upon when hiring each individual worker nowadays, and given the competitive market for tech workers, they tend to be matched across the industry (similarly to the base salary).⁶ Therefore, per-employee benefits are assumed to be fixed – unlike benefits issued through initiatives, which are external to contracts and can be designed with greater flexibility. Furthermore, the fact that initiative-based benefits are external to contracts means that they are more likely to be able to affect employee performance, particularly since employees often receive the benefit free of tax.⁷ Our second reason for focusing on initiative-based benefits is that this strategy has become increasingly popular in recent years, particularly in the high-tech sector, such that it is worthwhile analyzing the effect of this approach independently of other forms of compensation. Note, that our model focuses on any initiative-based non-salary benefit that involves spending by the employer. These include indirect monetary benefits (e.g., free concerts by leading artists or lucrative excursions, see [17]) as well as intangible elements (such as providing work flexibility for new parents, or inducing a positive working atmosphere, e.g., the slides installed in many Google offices, see [33]).

³ As Google Play is banned in China, see <https://www.businessofapps.com/data/app-stores/>.

⁴ <https://support.google.com/googleplay/android-developer/answer/112622?hl=en>; <https://developer.apple.com/programs/whats-included/>.

⁵ By the last quarter of 2022, over 3.5 million and 1.6 million applications were available on Google Play and App Store, respectively (<https://www.statista.com/statistics/276623/number-of-apps-available-in-leading-app-stores/>).

⁶ <https://www.betterup.com/blog/types-of-employee-benefits>.

⁷ See, for example, the terms in the USA: <https://digit.business/financial-literacy/office-christmas-parties-fringe-benefits-tax>; or the UK: <https://www.gov.uk/tax-company-benefits/taxfree-company-benefits>.

Given the recent rise in popularity of initiative-based benefits in the form of substantial spending [17], combined with the theoretical framework developed in this study, our paper provides a unique and important outlook on the potential value of such benefits both for employee recruitment and for the achievement of quality. To the best of our knowledge, this study is the first to introduce non-salary benefits into a model of the interaction between parties in a supply chain.

Using the mean-risk framework to model the developer’s risk attitude (proved to be consistent with second-degree stochastic dominance by [38]), we aim to answer the following research questions:

- How does the developer’s attitude towards risk affect the parties’ decisions, as well as their expected profits, at equilibrium?
- How is the developer’s budget divided, at equilibrium, between investing in product quality and funding non-salary benefits to employees, and which factors affect this allocation?

The rest of the study is structured as follows. Section 2 reviews the relevant literature, thereby highlighting the original contribution of this study. In Section 3, we construct the analytical model of the two-agent system, while in Section 4, we present its results at equilibrium. Section 5 extends the primary model to include multiple competing developers, thus strengthening the robustness and applicability of our analysis. Lastly, Section 6 expands upon the conclusions and managerial implications derived from our results, and offers potential directions for future study.

2. Literature review

The present study relates to three main areas of research: (a) non-salary compensation and its effect on employee performance; (b) supply chains of virtual products; and (c) the mean-risk criterion. The following sections review the existing literature under each of these domains. Key relevant studies are mapped and classified by their characteristics in the Author-contribution table below Table 1.

2.1. Non-salary benefits and their effect on employee performance

A multitude of empirical studies have found a positive correlation between wage and productivity, as firms minimize their labor costs while maintaining efficiency [28]. Levine [32] further elaborated on this hypothesis, and proved empirically that the increased productivity following a salary increase more than offsets the increase in labor costs. Most recently, Mariev et al. [35] tested the effect of several factors on worker productivity in various Russian firms, including from the high-tech sector. Interestingly, they found that salary was the most important factor influencing a worker’s willingness to contribute. Yet, Fisher et al. [19] showed that a salesperson’s performance reaches saturation once they are paid beyond a specific threshold.

In contrast, literature on non-salary benefits is rather limited. Schmidt-Sørensen [40] introduced non-salary benefits into the basic efficiency-wage model, on the basis that they were becoming a more prominent share of labor costs. His theoretical analysis highlighted the complex effect of such benefits on productivity, which may explain why later studies do not produce consistent findings. On the one hand, Gilchrist et al. [23] discovered, using an empirical approach, that unexpected and unconditional benefits given to workers boost productivity in a similar manner to hiring additional workers. An empirical study of American university staff showed that college tuition waivers offered to the workers’ dependents increased both retention and productivity [41]. On the other hand, Sung and Choi [42] found that when employers fund external education for workers (as opposed to internal training), the organization’s innovation performance can deteriorate.

Our study, to the best of our knowledge, is the first to consider initiative-based benefits in the high-tech sector. Under the assumption that such benefits have an uncertain yet notable effect on productivity as

Table 1

Author-contribution table (N/A denotes not applicable).

Authors	Stackelberg game	Nash game	Horizontal competition	Wholesale price contract	Revenue-sharing contract	Linear cost function	Quadratic cost function	Uncertain cost function	Risk investigation
[3]	V			V	V		V		MV
[4]	V	V	V		V	V			MV
[10]	V			V		V			UF
[26]	V			V			V		N/A
[1]	V				V		V		MV
[25]		V		V			V		MV
[11]	V				V			V	N/A
[2]	V				V		V		MV
Current paper	V	V	V		V		V	V	MR

Risk investigation legend: UF – Utility Function; MV – Mean Variance; MR – Mean Risk.

expressed through app quality, we use the mean-risk framework to analyze the decisions of the developer, who is an employer acting under uncertainty. Unlike the empirical approach taken by almost all previous papers on non-salary benefits (except for [40]), our model provides an analytical investigation of the topic.

2.2. Supply chains of virtual products

The rollout of advanced technologies in the 21st century resulted in a surge of new categories of intangible goods, commonly classified as virtual products [9]. Unlike tangible products, which involve inventory, delivery, distribution and other costly procedures, the supply of virtual products is carried out instantaneously at negligible unit cost [3,4]. These unique features have piqued the curiosity of numerous researchers in the fields of operations and supply-chain management.

Most researchers considered a two-echelon chain, consisting of a manufacturer (often an app/software developer) and a distributor (e.g., a platform or retailer), which operates under a Stackelberg game led by either the distributor [1–4,11,26] or the manufacturer [10]. The interaction has generally been analyzed under either a fixed-fee contract (relevant to supply chains of mobile games; see [25,26]) or a commission-rate contract (relevant to mobile apps; see [3]). Only a few studies introduced additional members into the chain, such as an investor [1], another platform [12] or multiple competing developers [4].

Avinadav et al. [3] recognized the effect of quality on demand in such chains – along with the possibility of influencing this relationship via quality investment. Most subsequent studies considered the virtual product's price, and either the investment in quality or the desired level of quality, as the sole influencers of demand – where these decisions are commonly assumed to be set by the manufacturer. To prevent the scenario where the investment in quality at equilibrium is infinite, the cost of quality is usually considered to take on a quadratic form (assuming diminishing returns; see [1]). Other variables that have been considered include the sales effort [25] and marketing investment [26]. Chernonog [11] further generalized these decisions into a vector of activities to be performed, with the goal of influencing either the revenue or the costs.

The involvement of uncertainty in the majority of operational decisions [14] has led researchers to incorporate it into their theoretical analyses of supply chains of virtual products. Many researchers have investigated uncertain demand by incorporating a random variable into the deterministic demand function, using either addition or multiplication (e.g., [2–4]). Using the mean-variance (MV) criterion to represent the attitudes of supply-chain members towards risk, most authors have reported that the retailer's risk attitude is irrelevant to equilibrium decisions due to the retailer's profit structure (e.g., [3]). Only Chernonog [11] has investigated uncertainty with respect to the cost of creating quality. In particular, she assumed that, under information asymmetry, the retailer estimates the manufacturer's cost function. Information asymmetry has also been considered in other recent studies of supply

chains of virtual products [2,26].

Our study makes a unique contribution to the existing literature, as we introduce a new decision variable – the non-salary benefits offered by the developer to his/her employees, which does not directly affect the demand for the app. Specifically, we capture the uncertain nature of the effect of non-salary benefits on the cost of quality (using a random variable). In addition, our model incorporates multiple developers within the supply chain, a scenario that has rarely been investigated in previous publications (aside from [4]). Note that our decision to ignore both the costs and the risk attitude of the platform is in line with the findings of the aforementioned studies.⁸

2.3. The mean-risk criterion

Decision-making under uncertain conditions inevitably reflects the decision-maker's attitude towards risk. If only the expected value of the decision's outcome is considered, then this reflects risk-neutral behavior, thereby ignoring the risk-averse or risk-seeking patterns that frequently characterize decision-makers. Having made this observation, the Nobel laureate Markowitz created the MV criterion for financial decisions, which considers the spread of the random variable in the form of its variance [13]. Walls and Dyer [44] later showed empirically that the MV criterion successfully predicts optimal decisions across industries.

In order to focus the analysis on negative outcomes (which are central to risk attitudes), researchers often replace variance with semi-variance characteristics, such as the standard deviation (SD) or absolute semi-deviation of the random variable. The use of such modified MV criteria has been further justified by the finding that they are analytically consistent with the rules of second-degree stochastic dominance⁹ – unlike the original MV criterion [38]. Substituting variance with a different characteristic of the random variable's distribution (usually the SD, as in the financial calculation of VaR) is commonly referred to as the mean-risk (MR) criterion [13].

Over recent decades, studies in operations and supply-chain management have incorporated the MV criterion into their analyses of decisions under uncertainty [13]. As mentioned previously, chains of virtual products often consider uncertain demand, and the vast majority of studies have used the original MV criterion (e.g., [2,3]). The introduction of an investor as a third player in the supply chain led Avinadav and Bunker [1] to discover that the more risk-averse the developer, the

⁸ The platform is assumed to incur negligible distribution costs [4]. Additionally, numerous studies with similar formulations have concluded that the platform's attitude towards risk has no effect on decisions at equilibrium [1,3,4,10].

⁹ Ogryczak & Ruszczyński [38] limited this conclusion to cases where the "trade-off" coefficient λ is smaller than 1, given two possible uncertain alternatives for the decision-maker. Since our analysis considers only one, this limitation does not apply to our use of the criterion.

more likely he/she is to seek external funding.

Although studies of supply chains of tangible goods have evolved to incorporate MR analyses [14], research on supply chains of virtual products tends to adhere to the original MV criterion. Our study is original in its use of the MR criterion, while relying on its proven analytical credibility. The MR criterion has the potential to ease analytical processing [31] and yield results that are more intelligible than the basic MV criterion.

As mentioned, uncertain costs in supply chains of virtual products have only been investigated in one previous study [11] and have never been examined using the MR criterion. To determine whether uncertainty has a positive or negative effect on a company's spending patterns (in terms of costs), we refer to several empirical studies conducted on the matter. Most of these detected a negative relationship, i.e., greater uncertainty leads to curbed spending – particularly for high uncertainty levels [6]. Moreover, greater risk-aversion levels were found to exacerbate this negative relationship [36]. Therefore, in the current study, where the MR criterion is used to model the developer's target function, the product of uncertainty (represented by the SD) and risk-aversion levels is subtracted from the expected value. Thus, we employ the same negative relationship as that adopted in previous MV applications (i.e., $E - \lambda V$), but note that in these applications, it was used to introduce uncertainty into other elements of the target function (e.g., uncertain base demand in [1]).

3. Model formulation

Consider a two-agent system of an app consisting of the app developer and a platform. Users can either acquire the app for free or at a cost, where in the former case, the app can generate revenue through one of the following methods: subscription fees (e.g., a subscription to the New York Times); a paid, premium version of the app; or in-app ads or purchases. Note that all notations used in this study appear in Table A in the Appendix, and key assumptions are summarized in the following subsection.

The demand for the app is affected by two elements – its quality, q , and the average revenue per user (ARPU), p . Specifically, the demand is given by

$$D(q) = a\sqrt{q} - ap \quad (1)$$

where a is the market scale parameter, and α represents the sensitivity of demand with regard to p . In line with existing literature, we use the square root function to convey the diminishing returns of consumers from the app's quality level [1]. The ARPU of the app (representing the revenue generated by the app per user from all its potential sources) is assumed to be exogenous, reflecting the intense competition among apps [39]. Logically, it has a negative linear effect on demand (since the ARPU is equivalent to the unit-price variable used in [3,9], and [10]). By using the ARPU to represent p , we accurately reflect reality in the sense that apps tend to make use of diverse revenue streams, in line with the current industry standard. In contrast, the aforementioned studies (listed in the previous set of parentheses) artificially constrained their models such that only paid apps were considered. Similar to those studies, we introduce the parameter α , which for paid apps simply stands for the price sensitivity of demand. For free apps, however, we assume that a higher ARPU would imply that the user's welfare is reduced in a similar fashion to when paying a higher selling price (through more ads, higher subscription fees, etc.), and the extent of this effect is depicted through α . Note that the demand for the app is deterministic throughout our analysis, despite the rarity of such a scenario in real life. This assumption however allows us to focus on uncertainty tied to cost (rarely discussed in closely related literature, e.g., [11]), while maintaining satisfactory resemblance to the behavior of an uncertain demand function.

The developer, in order to develop the app and position it competi-

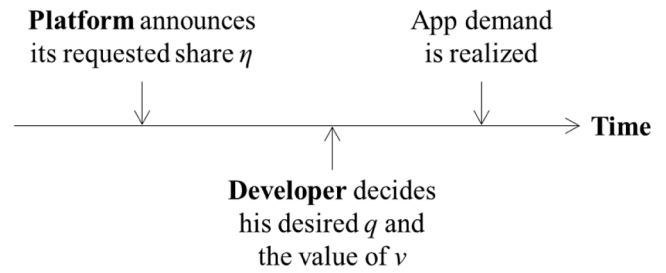


Fig. 1. The sequence of events.

tively on the market, invests in quality incurring the following cost:

$$C(q, v) = \frac{\varepsilon}{v} \rho q^2 \quad (2)$$

where ε is a normally distributed random element with mean 1, v is the amount that the developer spends on non-salary benefits, and ρ is a scale parameter represents the developer's economic efficiency in translating the invested sum into quality. The cost of creating quality clearly depends on the desired app-quality level, q , and the assumed quadratic relationship reflects the expected diminishing returns of quality investments [18,34]. The efficiency in achieving the desired quality level has been assumed to be constant by previous researchers (e.g., [1,25]), ignoring the possibility that its value might change according to the decisions of the developer. Therefore, our model breaks down the efficiency in creating quality into two elements. With respect to ρ , the higher its value, the more costly it would be to achieve a desired quality level. The fraction ε/v corresponds to the presumed effect of non-salary benefits on the creation of app quality by the developer's employees. We assume that v (the amount that the developer spends on non-salary benefits) has a hyperbolic effect¹⁰ with regards to the efficiency in achieving quality, expressed through the reciprocal presence of v in Eq. (2). Namely, the marginal worker efficiency gained from increasing v when it is already high, is smaller than when v is initially of a low value (following the findings of Fisher et al., 2006¹¹). Considering the previously-discussed uncertain effect of v , we introduce a normally distributed random variable over the vicinity of one, expressed by $\varepsilon \sim N(1, \sigma^2)$. We further assume that $\sigma \leq 0.33$, such that the probability of ε being negative is sufficiently small to be disregarded. In so doing, we reflect the assumption that benefits offered to employees result in some positive marginal utility for the average worker.

Using a Stackelberg non-cooperative sequential game, we model the interaction between the two members of the chain as presented in Fig. 1. The two largest platforms in the world for apps – Apple's App Store and Google Play – offer a non-negotiable contract to app developers, which

¹⁰ The hyperbolic function, expressed through the appearance of the variable in the reciprocal, has been chosen for its following two characteristics to represent the relation between v (the amount that the developer spends on non-salary benefits) and the efficiency coefficient for creating quality: (a) It decreases with respect to the variable, i.e., greater spending on non-salary benefits increases efficiency. (b) Its increments are smaller as the values of the variable increase, similar to law of diminishing returns, i.e., when efficiency is low – spending on non-salary benefits would improve it more significantly than when efficiency is already high, as a more substantial spending is required to increase it in the same manner. Furthermore, the function allows to reach analytical solutions to our theoretical setup, leading to useful conclusions and implications. Additionally, the hyperbolic function has been used previously in Operations Management literature to demonstrate a similar effect [24].

¹¹ Their research is relevant only to a limited extent, since they did not focus on non-salary benefits. However, their finding of employee saturation from compensation fits the logic behind the law of diminishing marginal productivity.

allows these platforms to interact effectively with hundreds of thousands of app developers. At the core of the contract lies the revenue-sharing agreement, which secures the platform 15–30 %⁴ of the revenue generated from the app. Therefore, the first stage of the game is the platform's announcement of its desired fraction η ($0 < \eta < 1$). Note that the only options open to the developer are to accept or reject the contract entirely; hence, we only address the scenario in which the developer is willing to enter into the agreement (similar to [3,4,25]). At the second stage, the developer determines both q and v in preparation for his/her app being launched via the platform. Lastly, once the app has been launched, the demand is realized and the revenue is split between the two members of the supply chain. Deduction of the developer's costs from his/her share of the revenue (as the only party to incur costs in the analysis) results in the following profits for the platform and the developer, respectively:

$$\pi_p(\eta) = \eta pD(q) \quad (3)$$

$$\pi_d(q, v) = (1 - \eta)pD(q) - v - C(q, v). \quad (4)$$

Note that v appears in the developer's profit function as an independent cost (in addition to its effect on the aforementioned efficiency in creating quality). Therefore, v does not include common per-employee non-salary benefits (e.g., health insurance, pension plans), which are hardly adjusted (if at all) by high-tech employers due to their commitment to matching the market's hiring standards. Naturally, salary-related benefits (such as bonus payments) adhere to similar market pressures [20], and consequently cannot be viewed in the same manner as v , i.e., as an independent cost and decision variable.

Furthermore, we assume that issuing initiative-based benefits (e.g., costly and lengthy vacations abroad, [17]) does not aim to improve outgoing quality directly,¹² albeit their regarded possible effect on its cost. Salary rates and salary-related benefits, on the other hand, are deployed predominantly as instruments for leveraging employee performance¹³ (i.e., for influencing the quality of the output). Therefore, any spending that is primarily intended to improve quality (including increased salaries, improved equipment, and training) appears under the cost of quality $C(q, v)$ (and not under v). To summarize, our unique formulation captures all significant costs associated with running a contemporary app-development firm.

3.1. Key assumptions

- The platform incurs negligible marginal costs.
- Demand is proportional to the square-root of the quality level of the app.
- The app's ARPU is exogenously determined by market forces.
- The cost of quality creation is proportional to the square of the app's quality level.
- The developer's spending on non-salary benefits has a hyperbolic effect on the efficiency in creating quality.
- Initiative-based benefits do not aim to improve app quality directly.

4. Equilibrium results

Each player's objective is to maximize its own expected utility by fine-tuning its respective decision variables. We adopt the MR criterion as a surrogate utility function for the developer, who faces cost uncertainty, as it captures the preference for a high expected profit and a low SD of the profit. Since the parties' decisions are made in two stages (see

Fig. 1), we use backward induction to reach equilibrium. This well-used method aligns with the nature of the sequential game lead by the platform (as used by the vast majority of researchers in the field, e.g., [2–4, 26]), namely, the platform sets the contract term by extrapolating the developer's decisions (i.e., best response) – in contrast to a Nash Equilibrium, in which the parties make their decisions simultaneously (see Section 5).

4.1. Second stage of decision making: the developer sets v and q

As illustrated in Fig. 1, the developer makes his/her decisions only after the platform has announced the contract term, i.e., the developer is the second party to move in the sequential game. The developer sets v (the monetary value of non-salary benefits to his/her employees) and q (the app's desired quality level) simultaneously, aiming to maximize the utility of his/her profit, as captured by the mean-risk criterion. The criterion expresses the desire of the developer to obtain a high expected profit while, at the same time, avoiding uncertainty, which is captured by subtracting a proportion of the profit's standard deviation from its mean value. As in previous studies using the MV criterion (e.g., [1]), λ (where commonly, $|\lambda| \ll 1$; see, e.g., [3]) represents the developer's level of risk aversion (when positive) or risk-seeking behavior (when negative), while σ stands for the SD of the random element.

For simplicity of presentation, we substitute the expression $(1 + \lambda\sigma)$ with ψ , which is of positive value throughout our entire analysis (see Appendix). Then, by inserting ψ into Eq. (4), alongside the demand function in Eq. (1) and the cost of quality in Eq. (2), we arrive (as detailed in the Appendix) at the following formulation of the developer's optimization problem with regard to the mean-risk of his/her profit:

$$\max_{q, v} \left\{ MR_d(q, v) = (1 - \eta)p(a\sqrt{q} - \alpha p) - v - \frac{1}{\psi} \rho \psi q^2 \right\}. \quad (5)$$

Since $MR_d(q, v)$ is a concave function with a single local (which is also a global) maximum of (q, v) , we arrive at the following proposition:

Proposition 1. *The developer's best-response is given by*

$$q(\eta) = \frac{1}{\rho\psi} \left(\frac{ap(1 - \eta)}{4} \right)^2, \quad v(\eta) = \frac{1}{\sqrt{\rho\psi}} \left(\frac{ap(1 - \eta)}{4} \right)^2. \quad (6)$$

Proof. See Appendix.

The decision variables at equilibrium are proportional with coefficient $\sqrt{\rho\psi}$. It can be seen that, already at this stage, the expressions depend directly on all the parameters of the analysis with the exception of the price (equivalent) sensitivity of demand (α). The two decision variables are directly proportional to a^2 , p^2 and $(1 - \eta)^2$ (i.e., the square of the developer's revenue share). While $q(\eta)$ is proportional to the inverse of ρ and ψ , $v(\eta)$ is proportional to the square-root of their inverse. A larger market (a) or a greater fraction of the revenue for the developer ($1 - \eta$) logically leads to greater investments in both quality and employee benefits, as well as greater efficiency in creating quality (expressed by a lower value of ρ) or greater certainty in the efficiency of creating quality (a lower value of σ).

Since $\psi > 0$ for both negative and positive values of λ (i.e., for risk-seeking and risk-averse behaviors, respectively), our analysis is robust for both of these scenarios. According to Eq. (6), the less risk-averse the developer (which refers to decreasing $|\lambda|$ when $\lambda > 0$) or the more risk-seeking the developer is (increasing $|\lambda|$ when $\lambda < 0$), the greater his/her investments in both quality and employee benefits.

Note that the best response $q(\eta)$ is directly proportional to p^2 . In our analysis, however, the developer is merely a 'price-taker' and has no control over the price. That is, the developer adjusts his/her sources of revenue so as to match the market's ARPU (through the app's selling price, the in-app ad intensity, and the price of in-app purchases). This characteristic firmly reflects the reality observed in the vast majority of

¹² Primarily, initiative-based non-salary benefits are reportedly issued with the goal of recruiting "top quality new employees while retaining existing ones" [17].

¹³ <https://www.wtco.com/en-NL/Insights/2021/12/compensation-trends-spotlight-tech-and-media>.

app markets, which seem to closely resemble perfect competition.¹⁴ Nevertheless, we conclude that a higher (lower) market ARPU would push the developer to raise (reduce) his/her app's quality in order to match the customers' expectation of a higher (lower) utility from using the app (a phenomenon proved empirically for paid apps by [45]¹⁵).

4.2. First stage of decision making: the platform sets η

Based on the developer's best response (see Eq. (6)), the platform initiates the game by setting its desired commission rate ($0 < \eta < 1$), while aiming to maximize its profit. This simulates the platform's decision making in reality, setting the contract terms for its millions of app developers, aiming to assess how they would react prior to making its final decision. This estimation would have been conducted to set the current terms for both existing and new apps, standing at 15–30 % on Google Play and App Store. Highlighting the importance of the platform's decision, amending existing terms rarely takes place nowadays due to its significant effect on the market, although recently both Apple and Google decided to lower the commission rate on their respective app stores for the majority of developers from 30 % down to 15 % [21]. Their decision is a direct result of predictions on the developer's best-response to new contract terms, primarily through his/her quality investments [1].

Unlike the developer, the profit of the platform is essentially deterministic since all its factors presented in Eq. (3) are independent of the random element ε . This comes as a result of the definition of the demand function as deterministic throughout our analysis, focusing on uncertainty related to the developer's efficiency in creating quality (see Section 3). Nevertheless, its profit is indirectly affected by this form of uncertainty due to the sequential nature of the game – utilizing the developer's aforementioned response to make its decisions, which indeed is tied to the random element (through the integrated parameter ψ , as indicated in Eq. (6)). Therefore, it is possible to express the platform's profit by simply inserting the demand function (1) into Eq. (3), while incorporating the developer's best response for $q(\eta)$, given in Eq. (6). Applying rudimentary algebraic reductions to the resulting expression leads the platform to solve the following maximization problem:

$$\max_{\eta} \left\{ \pi_p(\eta) = p^2 \eta \left(\frac{a^2(1-\eta)}{4\sqrt{\rho\psi}} - \alpha \right) \right\}. \quad (7)$$

The platform's profit is a concave function of η . Therefore, at equilibrium, it sets η to the value of the single maximum of $\pi_p(\eta)$, as presented in the following proposition:

Proposition 2. At equilibrium,

$$\eta^* = 0.5 - \frac{2\alpha}{a^2} \sqrt{\rho\psi}. \quad (8)$$

Proof. See Appendix.

4.3. Equilibrium results and discussion

Corollary 1. At equilibrium, the platform stipulates a commission rate that

is <50 % of the developer's revenue.

Proof. Straightforward from Proposition 2.

Interestingly, the commission rate at equilibrium illustrates a well-established practice in the world of apps. By Corollary 1, the platform would never set a commission rate in excess of 50 % of the developer's revenue, which is consistent with the reality that this rate typically ranges from 15 to 30 %⁴. This finding further testifies to the applicability of our analysis.

Corollary 2. At equilibrium, the platform's requested commission rate increases when

- The market scale parameter increases;
- The demand is less sensitive to price (or equivalent);
- The developer is more economically efficient in creating quality;
- Uncertainty with regard to the effect of non-salary benefits on quality creation is lower;
- The developer is either less risk-averse or more risk-seeking.

Proof. Straightforward from Proposition 2.

The conclusions of Corollary 2 seem to follow common sense, and resemble some of the findings of previous papers (e.g., [1]). In essence, the platform permits itself to charge a higher commission rate when the developer's circumstances are better, i.e., serving more customers, serving customers who are less sensitive to price (or, interchangeably, ARPU), enjoying greater certainty, or producing quality more efficiently. Similarly, the platform's commission rate increases when the developer is either less risk-averse (which would mean that $|\lambda|$ declines when $\lambda > 0$) or more risk-seeking ($|\lambda|$ grows when $\lambda < 0$). This apparent pursuit of a fair rate corresponds to the fact that the developer cannot enter into negotiations with regard to the platform's requested commission rate – both in our analysis and in reality⁵ (as well as in previous literature; see, e.g., [3,4]).

By inserting the value of η^* from Proposition 2 into the aforementioned expressions (followed by algebraic manipulations), we arrive at the equilibrium values for the developer's decisions, the developer's cost of creating quality, and the parties' profits:

Corollary 3. At equilibrium:

- The developer's decisions are given by $q^* = \frac{1}{\rho\psi} \left(\frac{p(a^2 + 4\alpha\sqrt{\rho\psi})}{8a} \right)^2$, $v^* = \frac{1}{\sqrt{\rho\psi}} \left(\frac{p(a^2 + 4\alpha\sqrt{\rho\psi})}{8a} \right)^2$;
- The developer's expected cost of creating quality is given by $E[C(q^*, v^*)] = \frac{1}{\psi\sqrt{\rho\psi}} \left(\frac{p(a^2 + 4\alpha\sqrt{\rho\psi})}{8a} \right)^2$;
- The platform's profit and the developer's expected profit are given by $\pi_p(\eta^*) = \frac{1}{\sqrt{\rho\psi}} \left(\frac{p(4\alpha\sqrt{\rho\psi} - a^2)}{4a} \right)^2$, $E[\pi_d(q^*, v^*)] = \frac{p^2(a^2 + 4\alpha\sqrt{\rho\psi})(a^2(3\psi - 1) - 4\alpha(5\psi + 1)\sqrt{\rho\psi})}{64a^2\psi\sqrt{\rho\psi}}$;
- The expected value of the profit of the channel is given by $E[\pi_{ch}(\eta^*, q^*, v^*)] = \frac{p^2(a^4(7\psi - 1) - 8\alpha\sqrt{\rho\psi}(a^2(5\psi + 1) + 2\alpha(\psi + 1)\sqrt{\rho\psi}))}{64a^2\psi\sqrt{\rho\psi}}$.

Proof. Straightforward from Proposition 2, along with Eqs. (5), (6) and (7).

Proposition 3. At equilibrium, $v^*/E[C(q^*, v^*)] = \psi$; Thus, the following statements apply to the uncertainty σ and the developer's level of risk sensitivity λ :

- These are the only parameters that affect the developer's allocation of his/her spending between product quality and non-salary benefits;

¹⁴ App markets meet most of the conditions of perfect competition (see [39]): millions of independent app developers and consumers; most apps have a multitude of nearly identical competitors; developers and consumers have abundant information about the apps (mostly available via the platform); very few barriers to enter/leave the market (<https://www.investopedia.com/terms/p/perfectcompetition.asp>, and [30]).

¹⁵ Zolkepli et al. [45] proved that "Users are [...] willing to pay for apps that have a higher rating"; these app star-ratings have been repeatedly used to indicate user-perceived quality (see [37]).

- ii. An increase (decrease) in the value of each parameter would result in the developer allocating a larger (smaller) share of his/her investment to non-salary benefits.

Proof. See Appendix.

Proposition 3 reveals a noteworthy characteristic regarding the developer's allocation decision, which lies at the core of this study. Although all equilibrium decisions and profits of both players (appearing in **Corollary 3**) depend on all of the model parameters (presented in **Table A** in the Appendix), the developer's allocation of resources (between non-salary benefits and the creation of quality) depends solely on two parameters. The first is the level of uncertainty, particularly with regard to the effect of investing in non-salary benefits on the efficiency of quality creation (as incorporated in **Eq. (2)**). Interestingly, the lower the level of certainty regarding this effect, the higher the developer's investment in non-salary benefits (instead of quality creation). A plausible analytical explanation for the developer's behavior is the desire to increase his/her deterministic spending (v) while reducing the uncertain cost of quality creation ($C(q, v)$). The second parameter, which is the developer's level of risk sensitivity, seems to follow a similar pattern. The more risk-averse (or less risk-taking) the developer, the lower the budget he/she allocates to quality creation, preferring instead to invest in non-salary benefits. Thus, the conservative developer prefers to invest in his/her workers, which is the safer alternative for enhancing efficiency in the long run. Our findings are consistent with evidence provided in various publications, highlighting that investment in human capital (particularly non-salary benefits) is a superior tool for boosting productivity to capital investments [22], particularly in uncertain times [5].

Given the central influence of both parameters encompassed within $\psi (\equiv 1 + \lambda\sigma)$ on equilibrium decisions, we hereby constrain its value in order to ensure that the platform's commission rate is a positive fraction ($0 < \eta^* < 1$). Since **Corollary 1** guarantees an upper limit for the commission rate of 0.5, it is only necessary to limit the parameters of its expression to ensure that $\eta^* > 0$. Performing rudimentary algebraic manipulations on this inequality, we state the following condition:

$$\psi < \frac{1}{\rho} \left(\frac{a^2}{4\alpha} \right)^2. \quad (9)$$

Corollary 4. While the platform's profit at equilibrium is always positive, the developer's expected profit is positive only when $a > 2\sqrt{\alpha\sqrt{\psi\sigma}}$, $\sqrt{\frac{5\psi+1}{3\psi-1}}$ and the channel's expected profit is positive only when $a > 2\sqrt{\alpha\sqrt{\psi\sigma}} \cdot \sqrt{\frac{5\psi+1+4\sqrt{\psi(1+2\psi)}}{7\psi-1}}$.

Proof. Straightforward from the expressions in **Corollary 3** and given the condition in **Eq. (9)**.

In line with the decision to disregard any costs associated with the platform (see **subSection 2.2**), by **Corollary 4**, the platform will always be positively rewarded as a result of interacting with the developer. On the contrary, the developer's expenses on quality creation and non-salary benefits lead him/her to lose when the above condition is not met. Combining the profits of the two, the entire channel could also experience losses, albeit for a less tight condition (because the platform always has a positive profit). Ultimately, the developer will lose when his/her market appears to be too small (i.e., when a is lower than the minimum stipulated in **Corollary 4**), although both the platform and the channel may still be profitable. Therefore, future studies could consider a scenario in which the platform further lowers its commission rate in

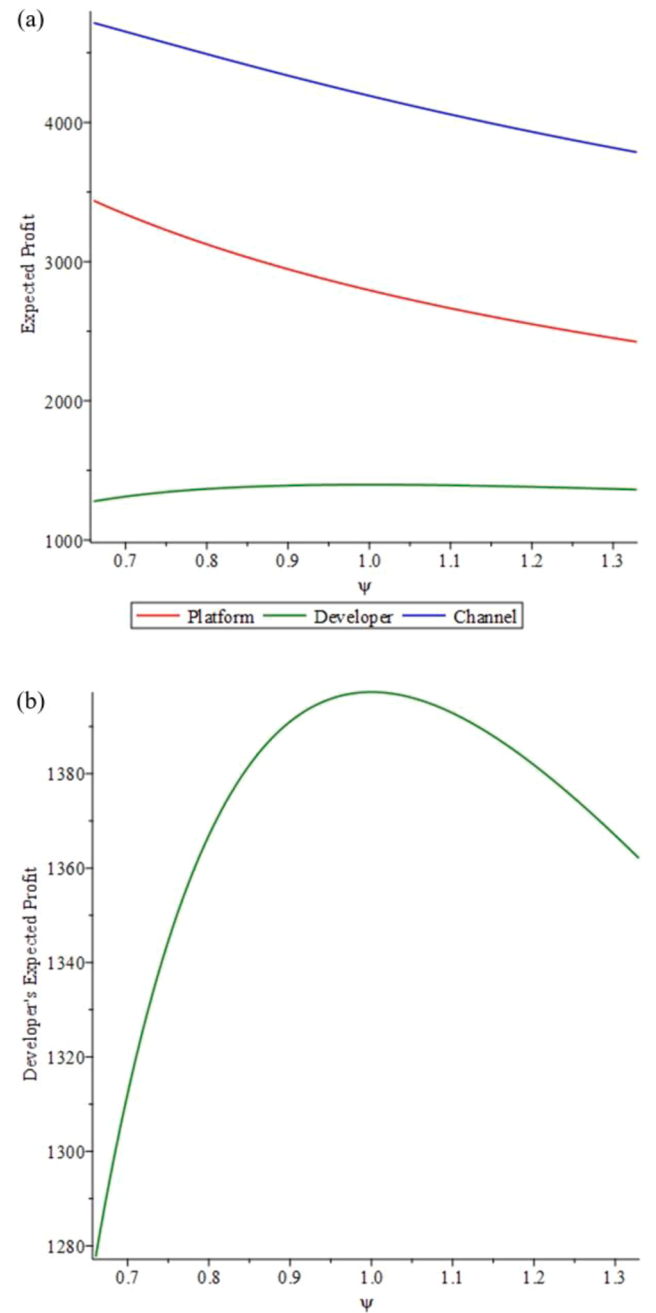


Fig. 2. The effect of ψ on the platform's, the developer's and the channel's expected profits. The setting used is $a = 100$, $p = 1$, $\alpha = 1$ and $\rho = 0.05$.

order to ensure that the developer can be profitable (e.g., by offering a side payment), thus making it worthwhile for the latter to operate under the non-negotiable contract of the platform.

4.4. Numeric exploration

Assuming that the developer's operations are profitable (i.e., the condition from **Corollary 4** is met), we are still unable to explore analytically the effect of $\psi (\equiv 1 + \lambda\sigma)$ on the players' profits (given the

non-linear effect of ψ on the profit expressions presented in Corollary 3). Therefore, we perform a numerical analysis for each expression that satisfies the condition in Eq. (9) and meets the additional conditions in Corollary 4. As demonstrated in Fig. 2, we use $a = 100$, $p = 1$, $\alpha = 1$, and $\rho = 0.05$ as the parameter values (resembling the numerical analysis of [1]) and vary the integrated parameter ψ between its extreme values ($0.67 < \psi < 1.33$; see Appendix). Note that our analysis also holds for more extreme parameter values.¹⁶

The platform's profit decreases (albeit nonlinearly) with an increase in ψ , meaning that the platform achieves lower profits as the developer becomes more risk-averse (i.e., as $|\lambda|$ grows when $\lambda > 0$ or as $|\lambda|$ declines when $\lambda < 0$). This finding replicates the results of multiple previous studies of app supply chains (e.g., [4]). However, the relation between the platform's profit and the level of uncertainty (particularly the level of uncertainty with regard to the effect of non-salary benefits on the efficiency of quality creation) is discontinuous. Specifically, when the uncertainty increases (i.e., higher σ) and the developer is more risk-averse (risk-seeking), the platform's profit will decrease (increase). Thus, the platform is harmed by non-salary ambiguity when the developer is risk-averse, but benefits from it when the developer is risk-seeking. This non-intuitive result implies that the platform would wish to increase the uncertainty faced by the risk-seeking developer with regard to the effectiveness of non-salary benefits. This could be achieved by the platform issuing such benefits to its own workers, and then entering into competition for employees with the developer. We therefore recommend that future studies should consider a platform that also acts as an employer of app developers (similarly to Apple and Google). The importance of studying this extension is further justified by considering the social planner's perspective, as the expected profit of the entire channel is dominated by the trend of the platform's profit (i.e., the channel's expected profit decreases in ψ similarly to the platform's profit).

Unlike the platform's and the channel's profits, the developer's expected profit behaves differently depending on whether the developer is risk-averse ($\lambda > 0$) or risk-seeking ($\lambda < 0$). Peaking around risk-neutrality ($\lambda = 0$ implying $\psi = 1$, see Fig. 2(b)), the expected profit decreases as the developer faces greater uncertainty (higher σ) or as the developer adopts a more extreme risk attitude (higher $|\lambda|$). Thus, the developer could consider adopting methods to reduce one (or both) of these parameters, such as business intelligence to determine the non-salary benefits offered by his/her competitors or objective decision-support systems (DSS)¹⁷ to allow the developer to adopt a more neutral attitude towards risk.

To strengthen the validity of our numeric exploration above, we have repeated the analysis for six additional settings of parameter values. In particular, we modified the values of p , a and ρ by 50 % above and below the original values used in this section (i.e., $p = \{0.5, 1.5\}$, $a = \{0.5, 1.5\}$ and $\rho = \{0.025, 0.075\}$), while keeping the other parameter values fixed (in order to isolate the effect of each parameter on the results). The effect of ψ on the platform's, the developer's and the channel's expected profits under this extended analysis appear in Figures A1-A6 in the Online Appendix. Comparing the results in Figures A1-A6 with those of Fig. 2 shows that our main findings are robust to such modifications of the parameter values.

5. Model extension: multiple developers

5.1. Introduction and market contextualization

Initiative-based non-salary benefits are granted primarily in order to

attract new workers and retain existing ones¹², as a response to global labor shortages – particularly in the high-tech sector. Employers are compelled to compete for the existing pool of capable workers, offering unconventional benefits in an attempt to win over major talents. Therefore, it is imperative to consider employer competition when discussing non-salary benefits. Moreover, researchers of supply chains of virtual products have rarely discussed competition between developers (one of the few studies that has considered such competition is [4]) and, to the best of our knowledge, have never considered competition between developers with regard to attracting employees.

We extend the original two-agent system to a system of N app developers who compete for employees through the use of initiative-based non-salary benefits. Note that throughout the following analysis, we use the same notations as those presented in Table A (see Appendix), while introducing the index i to denote the particular app developer (out of a total of N developers) to whom the variable or parameter applies. An additional adaptation involves the definition of α , which, from this point on, denotes the average price-equivalent sensitivity of demand for all the other ($N - 1$) competing apps. Lastly, we introduce parameter β ($0 < \beta < 1$) to represent the intensity of the competition between app developers for available employees; a higher value of β indicates that the employees working for a particular developer are more strongly influenced by the initiative-based non-salary benefits offered by competing developers (and vice versa for a lower value of β).

To allow for an elaborate analytical investigation, we consider app developers with similar values for all the parameters presented in Table A (see Appendix). Besides the universality achieved thanks to the analytical nature of our exploration (avoiding the resort to case-specific numerical analyses, e.g., for specific company sizes and markets), our concentration on developers with similar parameter values has been adopted by similar studies previously [4] as well as depicts real examples from the world of apps (see Table 2). Accordingly, our analysis focuses on app developers who serve the same category or market (i.e., with similar values for p , a , and α) and have comparable internal organization (similar ρ and λ). The level of uncertainty (represented through σ), particularly regarding the effect of investing in non-salary benefits on the efficiency of quality creation, is assumed to be identical for all developers given the lack of conclusive evidence on the matter across the entire industry, as well as to give rise to explicit results for the optimal solution. Since we wish to isolate the effect of employer competition, in this extension, we assume that the apps do not incur a purchase price (paid apps accounted for <6 % of available apps on Apple's App Store and Google Play in 2023),¹⁸ while the ARPU represents the per-user revenue from all non-price equivalents (e.g., the average revenue per user from viewing in-app ads).

Our setup closely resembles numerous notable examples from the world of competing apps, and several of them appear on Table 2. Specifically, the rivals on each category appear to share analogous characteristics that align with our assumption of identical parameters. Firstly, all apps are downloaded free-of-charge and offer in-app purchases of comparable sums (within each category), supporting our assumption of a shared p . When considered alongside with similar average revenues per user,¹⁹ it is possible to suppose that the demand faced by each app developer behaves similarly, i.e., with corresponding market scale (a) and price sensitivity (α). Lastly, the competing apps share a similar economic efficiency in creating quality (ρ), as reflected

¹⁸ Approximately 95% of mobile apps (both in Google Play and in Apple's App Store) are free to download: <https://www.statista.com/statistics/263797/number-of-applications-for-mobile-phones/>

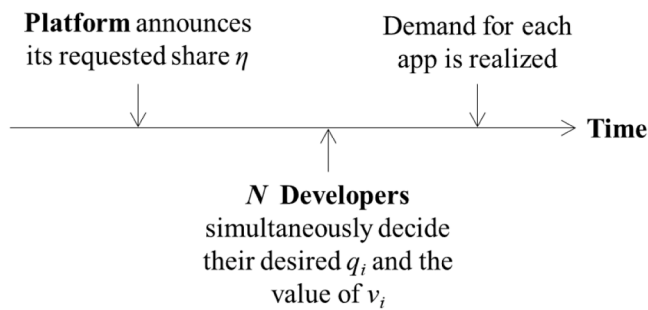
¹⁹ Commonly used to characterize the app's active user base: <https://www.appsflyer.com/glossary/arpu/>

¹⁶ We performed numerical analyses using parameter values much higher than those stated above, as well as values closer to those required to meet the condition in equation (9) and the additional conditions in Corollary 4.

¹⁷ <https://www.investopedia.com/terms/d/decision-support-system.asp>.

Table 2Comparison of the characteristics of rival app developers that largely conform to our assumption of having similar parameters¹.

Category ²	App	Average Price of In-App Purchases (USD) ³	Average Rating (out of 5) ⁴	Revenue Per Employee (thousands of USD) ⁵	Average Revenue Per User (USD) ⁶
Dating	Tinder	11.80	3.85	597	\$23.87
	Bumble	11.90	4.2	1290	\$18.06
Wellness	Headspace	40.80	4.7	439	\$110.00
	Calm	48.00	4.65	556	\$82.50
Social Networking	TikTok	7.23	4.6	1116	\$6.71
	Snapchat	12.75	4.45	1191	\$6.13

¹ All data were collected in the second week of August 2023.² As defined on: <https://www.businessofapps.com/data/app-sectors/>.³ The arithmetic average of all available in-app purchases presented in the Apple App Store (note that Google Play does not present this information): <https://www.apple.com/app-store/>.⁴ The arithmetic average of the rating (maximum 5 stars) given to the app on Apple's App Store (<https://www.apple.com/app-store/>) and on Google Play (<https://play.google.com/store/apps>).⁵ The ratio between the developer's annual revenue in 2022 (taken from <https://www.businessofapps.com/>) and his/her employee count (according to Zippia, ZoomInfo, Growjo, and Owler).⁶ The ratio between the developer's annual revenue and the number of active users (taken from <https://www.businessofapps.com/>).**Fig. 3.** The sequence of events when multiple developers compete for employees.

through both their per-employee revenues²⁰ and their star ratings on the app stores.²¹ Nevertheless, our analysis is not limited to the above examples, and might also resemble other rivalries in the world of apps.

5.2. Model formulation – multiple developers

As mentioned, this analytical investigation considers a two-agent system in which N app developers (who compete with each other for employees) distribute their individual apps via a single platform. A Stackelberg game takes place between the platform and the N app developers, among whom a Nash equilibrium exists. As shown in Fig. 3, at the first stage, the platform sets its universal commission rate (η , $0 < \eta < 1$), i.e., its requested fraction of the revenue gained from each app user. Subsequently, in preparation to launch their apps via the platform, all N developers set simultaneously (and non-cooperatively, as is the case for a Nash game) their desired app quality (q_i) and the amount they will spend on non-salary benefits (v_i). Finally, the demand for each app is realized concurrently – yet separately from the demand of its competitors, where the demand is expressed identically to the single-developer scenario presented in Eq. (1):

$$D_i(q_i) = a\sqrt{q_i} - ap \quad (10)$$

The decision to realize the demand separately for each app is based on real-world considerations. While nearly all apps can be downloaded for free²¹ (including those in Table 2), or offer a free version, most users tend to obtain several similar apps [43] in a category of their interest (e. g., news apps or puzzle games), which can also have the advantage of

maximizing the user's utility (e.g., in the case of multiple dating apps²²). Thus, the demand is not split between the apps of a given category, as most users are likely to contribute to the demand of multiple apps simultaneously. Moreover, apps within many categories compete on the basis of their unique brand and value proposition – features that do not necessarily correlate with higher spending on app quality (e.g., while Bumble is positioned as a female-centric platform, Tinder generally caters for more casual relationships – see [27]; similarly, different news apps could be classified as more/less conservative/liberal). Therefore, consumers simultaneously use multiple apps within a given category to accommodate (to differing extents) their diverse preferences. This highlights the absence of pure competition through quality in our setup and justifies the use of a separate demand expression for each individual app.

While the platform is assumed to incur negligible marginal costs [3, 4], each of the N app developers incurs costs related to app-quality creation:

$$C_i(q_i, v_i) = \frac{\varepsilon}{v_i - \frac{\beta}{N-1} \sum_{j \neq i} v_j} \rho q_i^2. \quad (11)$$

The cost incurred by each developer includes the same elements as those that comprise Eq. (2), namely, the desired quality level (q_i), the economic efficiency in creating quality (ρ), and the random variable (ε). Unlike Eq. (2), however, in the denominator of Eq. (11), we deduct from the developer's own spending on non-salary benefits (v_i) the average spending on such benefits by all other ($N-1$) app developers ($\frac{1}{N-1} \sum_{j \neq i} v_j$). Note that we multiply the latter quantity (the investment in benefits of the competing developers) by the parameter β , which implies that the denominator of the cost function decreases as the competition for employees increases. In other words, the marginal efficiency achieved through v_i diminishes when the average spending of competitors on such benefits is of a comparable dimension, particularly when employer competition is intense (e.g., the efficiency gain when the workers of a particular app developer attend a private concert of a known artist is lower if such a benefit appears to be standard among competitors). Subtracting the cost from the revenue of each developer leads to the following expression for their individual profits:

$$\pi_{d_i}(q_i, v_i) = (1 - \eta)pD_i(q_i) - v_i - C_i(q_i, v_i). \quad (12)$$

The profit of each app developer is composed of the developer's share of the revenue derived from his/her individual demand, decreased by his/her spending on non-salary benefits and quality creation (see the detailed discussion about the construction of the profit function in

²⁰ <https://www.investopedia.com/terms/r/revenueperemployee.asp>²¹ According to Kübler et al. [29], star ratings are valid estimates of app quality.²² <https://www.theknot.com/content/how-many-dating-apps>.

Section 3). The platform's profit is expressed as the sum of the commission fees collected across the set of N developers:

$$\pi_p(\eta) = \eta p \sum_{i=1}^N D_i(q_i). \quad (13)$$

To arrive at the equilibrium decisions of the players, we adhere to the sequential game in Fig. 3 and initially derive the developers' best-response decisions. We then use these values to extract the platform's commission rate at equilibrium, which, in turn, is substituted into the expressions for all other variables to complete the equilibrium.

5.3. Second stage of decision making: N developers set q_i and v_i concurrently

Once the platform has announced its commission rate, each developer prepares to launch the app via the platform by setting his/her desired quality level (q_i) and the amount he/she intends to invest in initiative-based non-salary benefits (v_i). As mentioned, all N developers decide upon these two variables simultaneously and non-cooperatively, reaching a Nash equilibrium. By incorporating the demand (Eq. (10)) and the cost (Eq. (11)) of each app developer into his/her individual profit function (Eq. (12)), we formulate the following maximization problem for each developer (using the MR criterion and substituting ψ , as described in subSection 4.1):

$$\max_{q_i, v_i} \left\{ MR_{d_i}(q_i, v_i) = (1 - \eta)p(a\sqrt{q_i} - \alpha p) - v_i - \frac{\rho\psi q_i^2}{v_i - \frac{\beta}{N-1} \sum_{j \neq i} v_j} \right\}. \quad (14)$$

Since the first-order condition (FOC) of each developer's optimization problem is symmetrical to that of every other developer (see Appendix), we express the symmetry in their individual decisions by removing the index from the variables; i.e., (q, v) represents the decision made by each individual developer. Hence, much like in the single-developer scenario, the developer's profit under symmetry is a concave function that has a single local (which is also a global) maximum, (q, v) , leading to the following proposition:

Proposition 4. Under symmetry, the best-response of each developer is given by

$$q(\eta) = \frac{1}{\rho\psi} \left(\frac{ap(1 - \eta)}{4} \right)^2, \quad v(\eta) = \frac{1}{\sqrt{\rho\psi}(1 - \beta)} \left(\frac{ap(1 - \eta)}{4} \right)^2. \quad (15)$$

Proof. See Appendix.

Interestingly, the best-response decisions of each developer are nearly identical to those in the absence of competition for employees, presented in Eq. (6). While the desired quality level $q(\eta)$ is unaffected by the level of competition, β , the competition parameter is included in the expression for $v(\eta)$. Specifically, and as would be expected, the more (less) intense the competition, the greater (smaller) the app developer's investment in non-salary benefits, to reflect the amount of effort that he/she needs to expend in attracting and retaining employees in accordance with the market trend. Moreover, the increasing hyperbolic effect of β on $v(\eta)$ implies that when the competition is already intense, the incremental increase in benefits as a function of β is significantly larger than when the competition is moderate. This insight might explain why companies already 'trapped' in the non-salary arena are pushed to constantly boost their nominal spending on such benefits. For example, if competitors offer dining experiences with the best local chefs, the developer will feel obliged to outperform them by offering dining experiences with an internationally-renowned (and more expensive) chef. Our analysis of the other elements in the expressions in Eq. (15) has already been presented in subSection 4.1 (see the discussion following Eq. (6)).

5.4. First stage of decision making: the platform sets η

Based on the computed best-response decisions of each developer (Eq. (15)), the platform sets its commission rate η ($0 < \eta < 1$) for the revenue-sharing contract that it offers to all app developers. Setting the commission rate is the platform's only decision and has the goal of maximizing the platform's profit. The introduction of competition into our model, under the aforementioned condition of symmetry between the developers (i.e., $\sum_{i=1}^N D_i(q_i) = N \cdot D(q)$), leads to the following expression for the platform's target function, which is obtained by inserting the demand function in Eq. (10) and the best-response quality function in Eq. (15) into the expression for the platform's profit in Eq. (13):

$$\max_{\eta} \left\{ \pi_p(\eta) = Np^2\eta \left(\frac{a^2(1 - \eta)}{4\sqrt{\rho\psi}} - \alpha \right) \right\}. \quad (16)$$

The platform's profit appears to be determined by multiplying its profit under the single-developer scenario (Eq. (7)) by the number of developers (N). This means that each developer contributes equally to the platform's profit (specifically, he/she contributes the amount given by Eq. (7)), and the total platform profit increases linearly in relation to the number of app developers on the platform. Accordingly, in common with the single-developer scenario, the platform's profit is a concave function of η (see Appendix) such that, at equilibrium, the platform sets η to the value corresponding to the single maximum of the profit function:

Proposition 5. At equilibrium, the platform charges a commission rate of

$$\eta^* = 0.5 - \frac{2\alpha}{a^2} \sqrt{\rho\psi}. \quad (17)$$

Proof. See Appendix.

5.5. Equilibrium results and discussion

Corollary 5. At equilibrium, the platform's commission rate is entirely unaffected by both the number of app developers and the level of competition between app developers for employees.

Proof. The value of η^* is identical when the platform interacts with one developer (Eq. (7)) and with N developers (Eq. (17)), and does not include the parameters N and β .

Although the platform's profit increases linearly with the number of app developers it contracts, by Corollary 5, its commission rate is set independently of this number (N). This finding supports the well-established use of universal commission rates by platforms. Therefore, in addition to the practical argument that setting a universal rate is an efficient means of interacting with millions of app developers, our analysis shows that for maximum profit at equilibrium, the commission rate indeed does not need to change as a function of the number of developers. We therefore complement the findings of Avinadav et al. [4] who showed that opting for a common-terms contract only slightly reduces the platform's revenue relative to quoting a different rate for each developer.

Corollary 5 also shows that the platform's decision regarding the commission rate is unaffected by the level of competition between app developers for available employees (β). However, it is worth noting that, nowadays, most leading platforms (including Apple and Google) are also major app developers, meaning that they are competing for talent along with the rest of the app development industry. Further investigation of this dual role of the platform under the condition of employer competition is recommended for future research.

We now reintroduce the index i to represent the equilibrium results for the i^{th} developer (out of N developers), in order to differentiate them from the results under the single-developer scenario stated above (while noting that the results under multiple developers still represent the

values under symmetry). Additionally, by [Corollary 5](#), the condition presented in [Eq. \(9\)](#) holds for the N -developer structure.

Corollary 6. *At equilibrium:*

i. The decisions of each developer are given by $q_i^* = \frac{1}{\rho\psi} \left(\frac{p(a^2 + 4\alpha\sqrt{\rho\psi})}{8a} \right)^2$,

$$v_i^* = \frac{1}{\sqrt{\rho\psi(1-\beta)}} \left(\frac{p(a^2 + 4\alpha\sqrt{\rho\psi})}{8a} \right)^2;$$

ii. Each developer's expected cost of creating quality is given by $E[C_i(q_i^*, v_i^*)] = \frac{1}{\psi\sqrt{\rho\psi}} \left(\frac{p(a^2 + 4\alpha\sqrt{\rho\psi})}{8a} \right)^2$;

iii. The platform's profit and the expected profit of each developer are given by $\pi_p(\eta^*) = \frac{N}{\sqrt{\rho\psi}} \left(\frac{p(4\alpha\sqrt{\rho\psi} - a^2)}{4a} \right)^2$, $E[\pi_{d_i}(q_i^*, v_i^*)] = \frac{p^2(2\alpha^2\rho\psi(\beta(4\psi+1)-5\psi-1)-a^2\alpha\sqrt{\rho\psi}(1+\psi-\beta)-0.125a^4(1-3\psi-\beta+4\beta\psi))}{8a^2\psi\sqrt{\rho\psi}(1-\beta)}$,

iv. The expected value of the profit of the channel is given by $E[\pi_{ch}(\eta^*, q_i^*, v_i^*)] = \frac{p^2(0.0625a^4(7\psi+\beta-8\beta\psi-1)-a^2\alpha\sqrt{\rho\psi}(2\psi(1.25-\beta)+0.5(1-\beta))-a^2\rho\psi(\psi-\beta+1))}{a^2\psi\sqrt{\rho\psi}(1-\beta)}$.

Proof. Straightforward from [Proposition 5](#) and [Eqs. \(14\), \(15\), and \(16\)](#).

By [Corollary 6](#), the expressions at equilibrium for the chosen quality level (q_i^*) and quality cost ($E[C_i(q_i^*, v_i^*)]$) of each developer are identical to those presented under the single-developer scenario (see [Corollary 3](#)). Thus, the quality level and cost of each developer are seemingly unaffected by the existence of competition for employees. However, the equilibrium investment of each developer in non-salary benefits (v_i^*) is different from that determined in the single-developer case (see [Corollary 3\(i\)](#)), specifically through the effect of β , as discussed previously. Therefore, the investment in app quality is indirectly affected by competition, as stated in the following proposition:

Proposition 6. *At equilibrium, $v_i^*/E[C_i(q_i^*, v_i^*)] = \frac{\psi}{1-\beta}$. Thus, the following statements apply to the level of uncertainty σ , the developer's risk-sensitivity level λ , and the intensity of employer competition β :*

- These are the only parameters that affect the developer's allocation of his/her spending between product quality and non-salary benefits;
- An increase (decrease) in the value of each of these parameters would result in the developer allocating a larger (smaller) share of his/her investment to non-salary benefits.

Proof. See Appendix.

The allocation decision of each of the N competing developers is affected by the same two parameters as in the single-developer scenario (see [Proposition 3](#)), with the notable addition of the parameter representing the intensity of employer competition (β). Since each developer splits his/her investment between quality creation and non-salary benefits to employees, intense competition for employees (high β) would compel developers to increase their spending on non-salary benefits. Consequently, their investment in app quality would consume a smaller proportion of their budget – as it is unaffected by employer competition at equilibrium (see [Corollary 6](#)). The current tendency for high-tech companies to invest heavily in initiative-based non-salary benefits [\[17\]](#) could reflect an extremely high value of β , and, in line with our findings, would also imply that equivalent investments in quality are less probable. Therefore, the results obtained under developer competition appear to reinforce our previous conclusions for the single-developer case, namely that investment in human capital is the superior tool for achieving success as a high-tech company [\[22\]](#). To summarize, non-salary benefits appear to be tied directly to each developer's bottom

line, and given the evident rollout of these benefits across the industry, we would recommend that the vast majority of app developers should consider instigating and competing through non-salary benefits in the form of initiatives. The human resources function of these companies could formally utilize such benefits to win the battle over available talent [\[8\]](#), potentially improving the company's competitive advantage altogether through the impact of talented employees on the output (see for software developers, [\[16\]](#)). Deployment of these benefits could be woven into the general marketing strategy as well, extending the reach for talent while positioning their app in line with the wanted brand image (e.g., apps targeting younger audiences could publicize fashionable artists brought to perform for their employees).

[Table 3](#) compares the equilibrium values of the variables in the single-developer setup (taken from [Section 4](#)) and the values in the N -developer setup. Accordingly, the table serves to isolate the changes resulting from the introduction of developer competition.

5.6. Numeric exploration

Unlike the platform's profit, the expressions for the developer's and the channel's profits ([Corollary 6](#)) are more cumbersome than those under the single-developer case ([Corollary 3](#)). To assess the effect of ψ on the profits, we replicate the setup of the numerical analysis in [Section 4](#) and we present the results in [Fig. 4](#). Given that the condition in [Eq. \(9\)](#) holds for our extension (η^* is identical), we use the same parameter values as under the single-developer setup, with the addition of $N = 4$. The parameter β varies between 0.01 and 0.99, with $\beta = 0.4$ for [Fig. 4](#) (a).

On the one hand, both the platform's and the channel's (expected) profits behave similarly to the single-developer case (compare [Fig. 2\(a\)](#) with [Fig. 4\(a\)](#)). On the other hand, the trend of the expected profit of each developer behaves differently in relation to ψ ($\equiv 1 + \lambda\sigma$), as depicted in [Fig. 4\(b\)](#). Although the profit of a risk-seeking developer ($\lambda < 0$, $\psi < 1$) still decreases the farther he/she is from risk-neutrality (i.e., the higher the value of $|\lambda|$) and the more uncertain the effect of non-salary benefits (i.e., higher σ), when employer competition is sufficiently intense (i.e., moderate to high values of β), his/her profit increases for the same reasons as when he/she is risk-averse ($\lambda > 0$, $\psi > 1$). That is to say, the developer's expected profits increase as he/she becomes more risk averse (higher λ) due to the fact that the platform charges a lower commission rate to compensate for the developer's risk aversion (see [Corollary 2](#), which is also applicable to the extension since η^* is identical). Presumably for the same reason, the higher the uncertainty associated with non-salary benefits faced by a risk-averse developer, the greater his/her profit. Therefore, an app developer who shares similar characteristics with his/her competitors (in line with our assumption of symmetry) and who faces substantial competition for employees, should actively increase his/her level of risk aversion, e.g., through hiring conservative managers (assumed to be naturally risk-averse) as the core decision-makers. Note that this unique scenario arises only when β is sufficiently large (approximately 0.4 in our analysis; see [Fig. 4\(b\)](#)). Below this threshold, the lower the value of β , the closer the behavior of the developer's profit to that observed in the

Table 3

The values of key variables under N competing developers, relative to the single-developer setup.

Variable	Ratio between the value with competition (Section 5) and without competition (Section 4)
Developer's app quality level	1
Developer's quality creation cost	1
Developer's spending on non-salary benefits	$\frac{1}{1-\beta}$
Platform's commission rate	1
Platform's profit	N

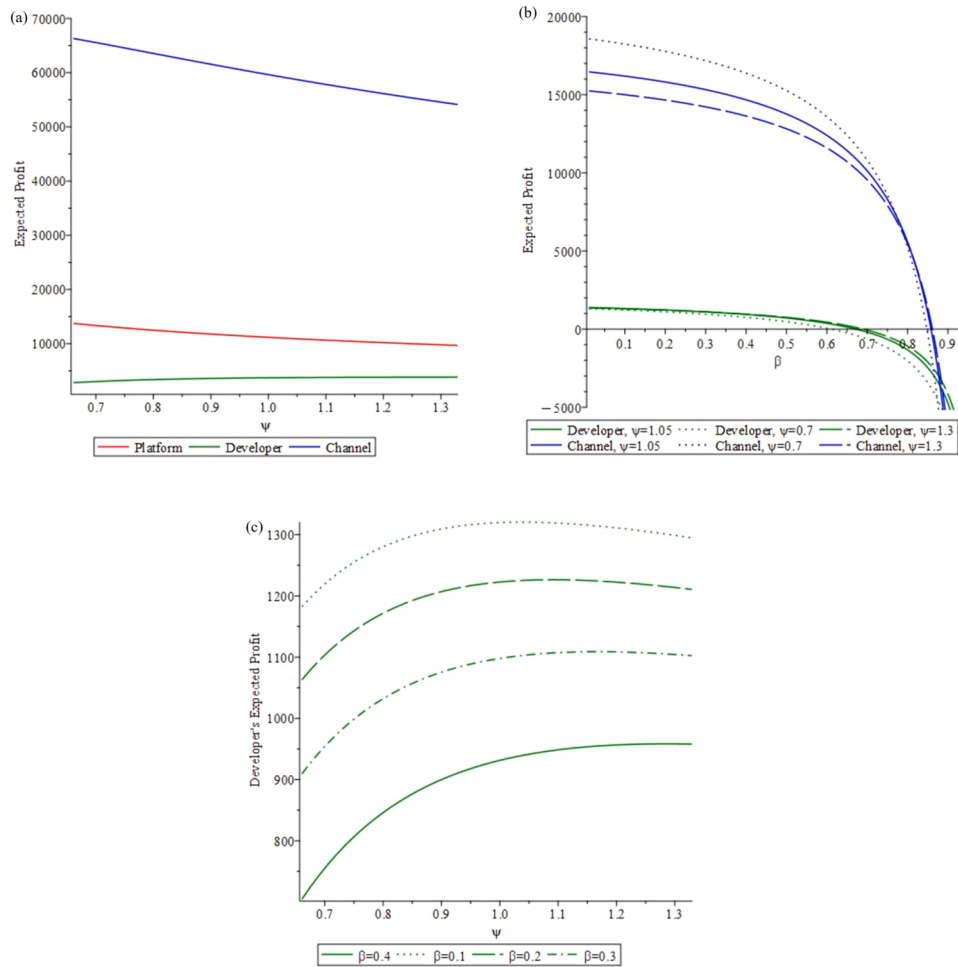


Fig. 4. The effect of (a) ψ on the platform's, the developer's and the channel's expected profits; (b) ψ on the developer's expected profits for $\beta = 0.4, 0.1, 0.2, 0.3$; (c) β on the developer's and the channel's expected profits for $\psi = 1.05, 0.7, 1.3$.

single-developer case (see Section 4) – that is, the profit is higher under risk-neutrality and when the uncertainty is lower.

Continuing with our analysis of the influence of employer competition, Fig. 4(b) and 4(c) present the effect of competition intensity (β) on the expected profits of each developer and of the platform. As is clearly shown in Fig. 4(c), above a certain threshold for β , the profits of each developer, as well as the profits of the channel, are negative. Consequently, the contract is not worthwhile for the developer when employer competition is too intense. Note that operating with a negative bottom line is a widespread practice in the world of apps,²³ meaning that the developer does not necessarily quit when his/her profit is negative. This result, however, reinforces our managerial conclusion from the single-developer scenario: it suggests that the platform, which is always positively rewarded, might consider lowering its commission rate further to sustain the app developers it contracts. In addition, the curves in Fig. 4(c) exhibit negative exponential growth, meaning that the profits are less affected by an increase in β when the latter is low than when it is high. This result reflects the manner in which β appears in the expression for $v(\eta)$, which calls for increasing increments in non-salary spending as a function of employer competition (see discussion in subSection 5.3).

6. Conclusions

Despite the popularity of non-salary benefits in the form of initiatives – both conventional and unconventional, particularly in the high-tech field – there are no existing studies that use analytical tools to explicitly examine the value of such a strategy. Building on previous analytical studies of supply chains of virtual products, we introduce non-salary benefits into this setup. We initially analyze a two-agent system composed of a platform and a single app developer, where the latter's target function is modeled using the mean-risk criterion. In an extension to the main model, and in order to reflect the real-world market situation, we then consider N symmetrical developers who are competing for available employees. The following summarizes our results of both the single-developer and the N -developer setups.

6.1. Research results and implications

The analysis reveals that the platform sets an identical commission rate regardless of the existence of developer competition. The rate, however, is chosen fairly, in accordance with the developer's circumstances, thereby supporting the common practice according to which prominent platforms offer a universal, non-negotiable contract (i.e., commission rate) to all app developers. The platform is always profitable; yet its profit decreases as the app developer becomes more risk-averse. While the platform benefits from uncertainty faced by a risk-seeking developer (particularly uncertainty regarding the effect of investing in non-salary benefits on the efficiency of quality creation), the

²³ Including some of the most highly valued apps globally, such as Uber, Lyft, Snap and Pinterest (<https://www.businessinsider.com/tech-companies-worth-billions-unprofitable-tesla-uber-snap-2019-11#6-pinterest-6>).

platform is harmed by such uncertainty when the developer is risk-averse.

The developer's allocation decision between quality creation and non-salary benefits, which lies at the core of this study, depends on his/her risk sensitivity, the level of uncertainty relating to non-salary benefits (see above), and the intensity of competition between developers for employees. When any of these parameters increases, the developer spends more on non-salary benefits for employees (without increasing his/her spending equivalently on app-quality creation). This noteworthy result analytically supports the philosophy of investment in workers as the organization's key long-term strategy, especially in times of uncertainty. Unlike the platform, the developer could face a loss; in general, however, he/she should aim to neutralize his/her risk attitude and lower the degree of uncertainty, potentially through relying on objective software for decision making (DSS). Nevertheless, we determine that a risk-averse developer facing moderate to high competition with symmetrical developers would actually benefit from a higher level of risk aversion and/or uncertainty. This takes place as the platform charges a lower commission rate to compensate the developers for their higher risk aversion. Thus, in this specific scenario, the developer should consider hiring or promoting risk-averse managers.

6.2. Future directions

Our results clearly highlight the need for all parties to examine the use of non-salary benefits throughout the app development market. In addition, we offer the following possible directions for future research in an attempt to characterize the current market with even greater accuracy. Firstly, we propose investigating stochastic demand functions, similarly to previous analytical studies on supply chains of apps.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at [doi:10.1016/j.orp.2024.100320](https://doi.org/10.1016/j.orp.2024.100320).

Appendix

Table A
Glossary of notations.

Variables	D	The demand function of the app
	C	The developer's cost of creating quality (random variable)
	π_p	The profit function of the platform
	π_d	The profit function of the developer (random variable)
	MR_d	Mean-risk of the developer's profit
	π_{ch}	The profit function of the entire channel (random variable)
Decision variables	ε	A normally distributed random element with mean 1
	η	The platform's commission rate from the revenue (set by the platform)
	q	The quality level of the app (set by the developer)
	v	The monetary value of non-salary benefits given to the developer's employees (set by the developer)
Parameters	p	The average revenue per user of the app (set exogenously)
	a	The market scale parameter
	α	The price-equivalent sensitivity of demand
	ρ	The economic efficiency of creating quality
	σ	The standard deviation of ε (< 0.33)
	λ	The developer's risk-sensitivity level
	ψ	An integrated parameter ($\psi \equiv 1 + \lambda\sigma$)

Proof – Sign of ψ

As mentioned in the Model Formulation section, we assume that $\sigma \leq 0.33$. In line with relevant previous literature (e.g., [3]), we state that $-1 < \lambda < 1$. Therefore, since $\psi = 1 + \lambda\sigma$, we conclude that the boundaries of the integrated parameter are given by $0.67 < \psi < 1.33$, milting that ψ is always positive throughout our analysis.

Development of the developer's objective function (Mean-Risk)

Secondly, our findings could be further generalized by considering multiple asymmetrical developers, as well as additional variables (e.g., technological advancement levels of each one). Thirdly, since the developer was found to face a loss under specific conditions – which might lead him/her to abandon the game – we suggest investigating one of the following two strategies to avoid this outcome: either the platform reduces its commission rate based on the developer's bottom line or the developer seeks financing from external investors. Furthermore, an interesting direction aiming at generalizing our model would be relaxing the assumption that the platform bears zero marginal costs, assessing its effect on the results in equilibrium. Lastly, we recommend performing empirical studies in attempt to validate our theoretical results in a real-life context. Given the analytical complexity of most of the model extensions suggested above, we expect that numerical analysis will need to be extensively used.

CRediT authorship contribution statement

Leonard Omer Maly: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Project administration, Methodology, Investigation, Formal analysis, Conceptualization. **Tal Avinadav:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization.

Declaration of competing interest

The authors declare that they have no conflicts of interests.

$$\begin{aligned}
MR_d(q, v) &= E[\pi_d(q, v)] - \lambda \sqrt{V[\pi_d(q, v)]} \\
&= E\left[(1-\eta)p(a\sqrt{q} - ap) - v - \frac{\varepsilon}{v}\rho q^2\right] - \lambda \sqrt{V\left[(1-\eta)p(a\sqrt{q} - ap) - v - \frac{\varepsilon}{v}\rho q^2\right]} \\
&= \left[(1-\eta)p(a\sqrt{q} - ap) - v - \frac{1}{v}\rho q^2\right] - \lambda \sqrt{\frac{\sigma^2}{v^2}\rho^2 q^4} \\
&= (1-\eta)p(a\sqrt{q} - ap) - v - \frac{1}{v}\rho q^2 - \lambda \frac{\sigma}{v}\rho q^2 \\
&= (1-\eta)p(a\sqrt{q} - ap) - v - \frac{1}{v}\rho(1 + \lambda\sigma)q^2 \\
&= (1-\eta)p(a\sqrt{q} - ap) - v - \frac{1}{v}\rho\psi q^2
\end{aligned}$$

Proof of Proposition 1

The leading principal minors of the Hessian matrix for $MR_d(q, v)$ are $D_1 = -\frac{2\rho\psi q^2}{v^3}$, $D_2 = \frac{\rho\psi\sqrt{q}pa(1-\eta)}{2v^3}$. Since the leading principal minor of even order (D_2) is positive, and that of uneven order (D_1) is negative, we conclude that the Hessian is negative definite, i.e., $MR_d(q, v)$ is a concave function with a single local maximum, which is also a global maximum. A simultaneous solution of the FOC ($\nabla MR_d(q, v) = \left(\frac{\partial}{\partial v}MR_d, \frac{\partial}{\partial q}MR_d\right) = \left(\frac{\rho\psi q^2}{v^2} - 1, \frac{pa(1-\eta)}{2\sqrt{q}} - \frac{2\rho\psi q}{v}\right) = (0, 0)$) leads to the following single maximum point:

$$q(\eta) = \frac{1}{\rho\psi} \left(\frac{ap(1-\eta)}{4}\right)^2, \quad v(\eta) = \frac{1}{\sqrt{\rho\psi}} \left(\frac{ap(1-\eta)}{4}\right)^2.$$

Proof of Proposition 2

Since $\frac{d^2}{d\eta^2}\pi_p(\eta) = -\frac{a^2 p^2}{2\sqrt{\rho\psi}} < 0$, $\pi_p(\eta)$ is a concave function of η with a single local maximum, which is also a global maximum. Solving the FOC, $\frac{d}{d\eta}\pi_p(\eta) = -\frac{v^2}{2} \left(\frac{a^2(\eta-0.5)}{\sqrt{\rho\psi}} + 2a\right) = 0$, leads to $\eta^* = 0.5 - \frac{2a}{a^2} \sqrt{\rho\psi}$. Therefore, at equilibrium, the platform maximizes its profit by setting η to this value.

Proof of Proposition 3

- Based on the results presented in Corollary 3(i) and 3(ii), the ratio $\frac{v^*}{E[C(q^*, v^*)]} = \psi = 1 + \lambda\sigma$. Therefore, the balance between these two elements (v^* and $E[C(q^*, v^*)]$) entirely depends on the degree of uncertainty – represented by the SD of the random variable (σ) and the risk sensitivity of the developer (λ).
- The above ratio is proportional to the product of σ and λ .

Proof – Symmetry of the N Developers

The FOC for maximizing $MR_{d_i}(q_i, v_i)$ is

$$\nabla MR_{d_i}(q_i, v_i) = \left(\frac{\partial}{\partial v_i}MR_{d_i}, \frac{\partial}{\partial q_i}MR_{d_i}\right) = \left(\frac{\rho\psi q_i^2}{\left(v_i - \frac{\beta}{N-1}\sum_{j \neq i} v_j\right)^2} - 1, \frac{pa(1-\eta)}{2\sqrt{q_i}} - \frac{2\rho\psi q_i}{v_i - \frac{\beta}{N-1}\sum_{j \neq i} v_j}\right) = (0, 0).$$

Thus, the decisions of each developer are derived from functions differentiated solely by the decisions of the other developers (i.e., through $\sum_{j \neq i} v_j$). Assuming an interior solution exists, we require symmetry among the decisions of all N developers; thus, we substitute the indexed decision variables with an unindexed pair, (q, v) , denoting the decisions made by every developer within our symmetrical setup.

Proof of Proposition 4

By substituting (q_i, v_i) with (q, v) to express the symmetrical decisions made by the developers, we are able to rewrite the original leading principal minors of the Hessian matrix for $MR_{d_i}(q_i, v_i)$ as $D_1 = -\frac{2\rho\psi q^2}{v^3(1-\beta)^3}$, $D_2 = \frac{\rho\psi\sqrt{q}pa(1-\eta)}{2v^3(1-\beta)^3}$. Since the leading principal minor of even order (D_2) is positive, and that of uneven order (D_1) is negative, we conclude that the Hessian is negative definite, i.e., $MR_{d_i}(q_i, v_i)$ under symmetry is a concave function with a single local maximum, which is also a global maximum. Solving the FOC

$$\left(\nabla MR_d(q, v) = \left(\frac{\partial}{\partial v}MR_d, \frac{\partial}{\partial q}MR_d\right) = \left(\frac{\rho\psi q^2}{v^2(1-\beta)^2} - 1, \frac{pa(1-\eta)}{2\sqrt{q}} - \frac{2\rho\psi q}{v(1-\beta)}\right) = (0, 0)\right)$$

results in the following single maximum point:

$$q(\eta) = \frac{1}{\rho\psi} \left(\frac{ap(1-\eta)}{4}\right)^2, \quad v(\eta) = \frac{1}{\sqrt{\rho\psi}(1-\beta)} \left(\frac{ap(1-\eta)}{4}\right)^2.$$

Proof of Proposition 5

Since $\frac{d^2}{d\eta^2}\pi_p(\eta) = -\frac{Na^2 p^2}{2\sqrt{\rho\psi}} < 0$, $\pi_p(\eta)$ is a concave function of η with a single local maximum, which is also a global maximum. Solving the FOC for

maximizing the platform's profit, $\frac{d}{d\eta}\pi_p(\eta) = -\frac{Np^2}{2}\left(\frac{a^2(\eta-0.5)}{\sqrt{\rho\psi}} + 2\alpha\right) = 0$, leads to $\eta^* = 0.5 - \frac{2\alpha}{a^2}\sqrt{\rho\psi}$.

Proof of Proposition 6

- i. Based on the results presented in Corollary 6(i) and 6(ii), the ratio $\frac{v_i^*}{E[G_i(q_i^*, v_i^*)]} = \frac{\psi}{1-\beta} = \frac{1+\lambda\sigma}{1-\beta}$. Therefore, the balance between these two elements entirely depends on the degree of uncertainty – represented by the SD of the random variable (σ), the risk sensitivity of the developer (λ), and the intensity of competition among developers for employees (β).
- ii. While the above ratio is linear in the product of σ and λ , it is a rising-hyperbolic function with respect to β ($0 < \beta < 1$).

Data availability

No data was used for the research described in the article.

References

- [1] Avinadav T, Bunker AE. The effect of risk aversion and financing source on a supply chain of in-app products. *Int Trans Oper Res* 2021;29(4):2145–71.
- [2] Avinadav T, Chernonog T, Meilijson IE, Perlman Y. A consignment contract with revenue-sharing between an app developer and a distribution platform. *Int J Prod Econ* 2022;243:108322.
- [3] Avinadav T, Chernonog T, Perlman Y. The effect of risk sensitivity on a supply chain of mobile applications under a consignment contract with revenue sharing and quality investment. *Int J Prod Econ* 2015;168:31–40.
- [4] Avinadav T, Chernonog T, Perlman Y. Consignment contract for mobile apps between a single retailer and competitive developers with different risk attitudes. *Eur J Oper Res* 2015;246(3):949–57.
- [5] Banholzer M, Dreischmeier R, LaBerge L, Libarikian A. Business building: the path to resilience in uncertain times. McKinsey & Company 2022. <https://www.mckinsey.com/capabilities/risk-and-resilience/our-insights/business-building-the-path-to-resilience-in-uncertain-times>.
- [6] Bo H, Lensin R. Is the investment-uncertainty relationship nonlinear? An empirical analysis for the Netherlands. *Economica* 2005;72(286):307–31.
- [7] Bradford L. 13 tech companies that offer cool work perks. *Forbes* 2016. <https://www.forbes.com/sites/laurencebradford/2016/07/27/13-tech-companies-that-offer-insanely-cool-perks/?sh=155ea02779d1>.
- [8] Carlin D, Madgavkar A, Maor D, Reich A. Overcoming the fear factor in hiring tech talent. McKinsey & Company 2022. <https://www.mckinsey.com/capabilities/people-and-organizational-performance/our-insights/overcoming-the-fear-factor-in-hiring-tech-talent>.
- [9] Chernonog T, Avinadav T. Profit criteria involving risk in price setting of virtual products. *Eur J Oper Res* 2014;236(1):351–60.
- [10] Chernonog T, Avinadav T, Ben-Zvi T. How to set price and sales effort in a supply chain of virtual products under bi-criteria and risk consideration. *Int J Prod Econ* 2019;209:156–63.
- [11] Chernonog T. Strategic information sharing in online retailing under a consignment contract with revenue sharing. *Ann Oper Res* 2021;300(2):621–41.
- [12] Chernonog T, Levy P. Co-creation of mobile app quality in a two-platform supply chain when platforms are asymmetric. *Eur J Oper Res* 2023;308(1):183–200.
- [13] Chiu CH, Choi TM. Supply chain risk analysis with mean-variance models: a technical review. *Ann Oper Res* 2016;240(2):489–507.
- [14] Choi T, Chiu C. Risk analysis in stochastic supply chains: a mean-risk approach (International series in operations research & management science. 2012th ed. Springer; 2012. p. 178.
- [15] Dal Bó E, Finan F, Rossi MA. Strengthening state capabilities: the role of financial incentives in the call to public service. *Q J Econ* 2013;128(3):1169–218.
- [16] Datta S. How does developer interaction relate to software quality? an examination of product development data. *Emp Software Eng* 2017;23(3):1153–87.
- [17] Dori R. Have tech companies gone too far with exorbitant perks to attract employees? CTECH; 2022. <https://www.calcalistech.com/ctech/articles/0,7340,L-3929178,00.html>.
- [18] El Ouardighi F, Kim B. Supply quality management with wholesale price and revenue-sharing contracts under horizontal competition. *Eur J Oper Res* 2010;206(2):329–40.
- [19] Fisher M, Krishnan J, Netessine S. Retail store execution: an empirical study. *SSRN Electronic Journal* 2006.
- [20] Francis T, Mickle T. Tech giants turn to a classic recruitment tool: cash. *The Wall Street J* 2022. <https://www.wsj.com/articles/tech-giants-turn-to-a-classic-recruitment-tool-cash-11645957980>.
- [21] Gartenberg C. Google will reduce Play Store cut to 15 percent for a developer's first \$1M in annual revenue. *The Verge* 2021. <https://www.theverge.com/2021/3/16/22333777/google-play-store-fee-reduction-developers-1-million-dollars>.
- [22] Garton E. The case for investing more in people. *Harv Bus Rev* 2018. <https://hbr.org/2017/09/the-case-for-investing-more-in-people>.
- [23] Gilchrist DS, Luca M, Malhotra D. When $3 + 1 > 4$: gift structure and reciprocity in the field. *Manage Sci* 2016;62(9):2639–50.
- [24] Hanukov G, Avinadav T, Chernonog T, Yechiali U. Performance improvement of a service system via stocking perishable preliminary services. *Eur J Oper Res* 2018;274(3):1000–11. <https://doi.org/10.1016/j.ejor.2018.10.027>.
- [25] Hu B, Meng C. The effect of risk tolerance in mobile game supply chain pricing and effort decisions. *J Oper Res Soc* 2021;72(10):2301–16.
- [26] Hu B, Liu L, Meng C. Information sharing in an online game supply chain. *IEEE Trans Eng Manage* 2020. <https://doi.org/10.1109/TEM.2020.3040767>.
- [27] Kalia A. Newly single? A beginner's guide to the best dating apps. *The Guardian* 2020. <https://www.theguardian.com/lifeandstyle/2019/dec/02/newly-single-a-beginners-guide-to-the-best-dating-apps>.
- [28] Katz LF. Efficiency wage theories: a partial evaluation. NBER 1986. Retrieved September 27, 2022 from, <http://www.nber.org/books-and-chapters/nber-macroec-economics-annual-1986-volume-1/efficiency-wage-theories-partial-evaluation>.
- [29] Kübler RV, Pauwels K, Yildirim G, Fandrich T. App popularity: where in the world are consumers most sensitive to price and user ratings? *J Mark* 2018;82(5):20–44.
- [30] Kung M, Monroe KB, Cox JL. Pricing on the internet. *J Product Brand Manag* 2002;11(5):274–88.
- [31] Lau HS. The newsboy problem under alternative optimization objectives. *J Oper Res Soc* 1980;31(6):525–35.
- [32] Levine DI. Can wage increases pay for themselves? Tests with a productive function. *Econ J* 1992;102(414):1102–15.
- [33] Lynley M. RANKED: the best slides and worst slides in Google's offices. *Business Insider* 2012. <https://www.businessinsider.com/googles-office-slides-2012-5>.
- [34] Perlman Y. Establishing a dual food supply chain for organic products in the presence of showrooming – A game theoretic analysis. *J Clean Prod* 2021;128816.
- [35] Mariev O, Nagieva K, Pushkarev A, Davidson N, Sohag K. Effects of R&D spending on productivity of the Russian firms: does technological intensity matter? *Empir Econ* 2021;62(5):2619–43.
- [36] Nakamura T. Risk-aversion and the uncertainty–investment relationship: a note. *J Econ Behav Organizat* 1999;38(3):357–63.
- [37] Noei E, Syer MD, Zou Y, Hassan AE, Keivanloo I. A study of the relation of mobile device attributes with the user-perceived quality of Android apps. *Emp Software Eng* 2017;22(6):3088–116.
- [38] Ogryczak W, Ruszczyński A. From stochastic dominance to mean-risk models: semideviations as risk measures. *Eur J Oper Res* 1999;116(1):33–50.
- [39] Petsas T, Papadogiannakis A, Polychronakis M, Markatos EP, Karagiannis T. Rise of the planet of the apps. In: *Proceedings of the 2013 Conference on Internet Measurement Conference*; 2013.
- [40] Schmidt-Sørensen JB. Non-wage labour costs and productivity shifts in an efficiency-wage-hours model. *Recherch Econ de Louvain /Louvain Econ Rev* 1991;57(2):205–11.
- [41] Spencer M, Gevrek D, Chambers V, Bowden R. Labor supply and productivity responses to non-salary benefits. *Personnel Review* 2016;45(5):1047–68.
- [42] Sung SY, Choi JN. Do organizations spend wisely on employees? Effects of training and development investments on learning and innovation in organizations. *J Organ Behav* 2013;35(3):393–412.
- [43] Unal P, Temizel TT, Eren PE. What installed mobile applications tell about their owners and how they affect users' download behavior. *Telemat Inf* 2017;34(7):1153–65.
- [44] Walls MR, Dyer JS. Risk propensity and firm performance: a study of the petroleum exploration industry. *Manage Sci* 1996;42(7):1004–21.
- [45] Zolkepli IA, Mukhiar SNS, Tan C. Mobile consumer behaviour on apps usage: the effects of perceived values, rating, and cost. *J Market Communicat* 2020;27(6):571–93.