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Revenue Management Practices in Peer-to-Peer Accommodation: The Case of Airbnb[1]

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Abstract

Purpose: Revenue management (RM) practices are well established in the hotel industry. Peer-to-peer (P2P) accommodation is a distinctive alternative to hotels, which in its original intention, is managed by non-professionals. The main research question of this study was how the professionalism of P2P accommodation providers relate to their use of RM practices.

Research method: I performed statistical analysis of 479,282 pricing records for 25,827 properties offered through Airbnb in the period of 67 months (August 2015 – February 2021) in Poland. Two indicators of hosts' professionalism (the number of properties they manage and the possession of superhost status) were tested against three RM practices (cancellation policy, minimum stay, and dynamic pricing).

Findings: This study clearly showed the intensification of P2P hosts' professionalization in comparison to previous research. Moreover, it proved that professional and non-professional hosts' behaviors significantly differ when it comes to RM practices application, but the discrepancies are not equally distinctive. The finding that brought a considerably different result in comparison to previous research was the negative relationship between a multi-unit host and minimum stay.

Implications and future research: This study should serve as a warning for hoteliers about the P2P hosts' professionalization, as they become equal competitors. There are several future extensions to this study, including holiday destinations, testing other than hosts' professionalism variables, or shedding light on the evolution of RM practices application could reveal valuable insights.

Originality: This study contributes to the existing research by offering the analysis of very recent longitudinal data and covering professional vs. non-professional P2P hosts' behaviors in terms of three RM practices in Central-Eastern Europe settings.

Keywords: revenue management, peer-to-peer accommodation, Airbnb, dynamic pricing.

JEL: M10, M39, L11, L25, D22

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Introduction

Although it originated from airlines, revenue management (RM) has spread into multiple service industries, including hotels. The objective of RM is to maximize the total revenue of the concerned service in accordance with demand management decisions on prices or the allocation of required resource (Talluri and van Ryzin, 2005).

Peer-to-peer (P2P) accommodation is a distinctive alternative to hotels, in its original intention managed by non-professionals. As a relatively new phenomenon, P2P constantly evolves and the research in this field is expanding fast (Belarmino and Koh, 2020).

The research on RM in P2P accommodation has so far mainly focused on dynamic pricing, while other practices have not been sufficiently studied. Hossain (2020) concludes that non-professional service providers (hosts) serve their guests in different ways, and he indicates that by comparing non-professional and professional hosts, future research may reveal valuable insights. Another conclusion is that most studies examine data from Airbnb and Uber in Western settings, so exploring sharing economy firms in the context of other countries, may importantly provide more balanced knowledge about sharing economy (Hossain, 2020). Moreover, the studies so far covered shorter periods and data until 2018. As the professionalization of the P2P accommodation providers unfolds dynamically, there appeared the need for more recent data analysis. The need for longitudinal data analysis is expressed by Belarmino and Koh (2020) in their recent critical review of research regarding P2P accommodation. Furthermore, Kwok and Xie (2019) advocate that future research that uses a broader range of markets than that of their study can validate and extend their findings, which they thus highly encourage. Sharing economy and P2P accommodation saw research in Central Eastern Europe conditions (see Pawlicz, 2019; Sztokfisz, 2018) but not in the context of RM.

Aggregating the above insights, this study adds to the existing research by offering the analysis of very recent longitudinal data (67 months until February 2021), covering professional vs non-professional P2P hosts' behaviors in terms of three RM practices in a Central Eastern European setting. The main research question for this study was: How the professionalism of P2P accommodation providers relates to their usage of RM practices?

Literature Review

Sharing Economy and Peer-to-Peer Accommodation

As a relatively new phenomenon, the sharing economy concept is constantly evolving and expanding into new industries and business models (Hossain, 2020). For this research, I applied the definition by Stephany (2015), which presents sharing economy as the value in taking underutilized assets and making them accessible online to a community, leading to a reduced need for ownership of those assets (Stephany, 2015). This definition comprises of five main components: creating reciprocal value, utilizing idling capacity, sharing online to the community that shows similar interests or engagement beyond their transactional needs, and allowing to reduce the necessity to own a given asset as a result.

When did old-fashioned house rental turn into sharing economy? As explained by Narasimhan et al. (2018), the turning point was the appearance of the Internet platform at the very heart of the transaction. What used to be a two-way transaction has become a three-way transaction. The platform brings buyers and sellers together, collects and disburses payments, and maintains the ratings-based reputation system that makes the sharing marketplace function. In the sharing economy, the Internet and newer mobile technologies enable buyers to immediately connect with tens or hundreds of service providers. Such access is provided at the time of choosing by the buyer. Service providers use multiple types of content such as text, photos, videos, and maps to provide more information about their offerings, and computer algorithms make the matching effective and efficient. Furthermore, buyers can access the experience of past users of a seller's product/service and similarly sellers can access the experience of past sellers with the particular buyer (Narasimhan et al., 2018).

Airbnb hosts typically join the platform because they have space that they are hoping to rent out for profit. Likewise, guests are often on the platform because they seek accommodation that is larger, better located, less artificial, and more affordable than hotels (Sundararajan, 2016). This way P2P accommodation offers the distinctive value to their customers, in contrast to hotels being managed by non-professionals, having much less experience, and almost no access to sophisticated RM tools.

Unlike many other sharing economy platforms, like Lyft and Uber, where an algorithm controls prices, Airbnb allows its individual hosts to decide whether they want to act on the tool's advice or not. The individual host control over pricing decisions creates

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a situation in which the hosts' characteristics and skills are as important as the property and market characteristics in determining the price (Gibbset al., 2018).

Revenue Management

Since the expansion of RM from airlines to the hospitality industry, a certain scope of practices typical to this sector have been adapted or developed. Among others, the practices include minimum length of stay controls, non-refundable advanced deposits, cancellation penalties, and dynamic pricing (Talluri and van Ryzin, 2005; Tranter, Stuart-Hill, and Parker, 2014; Vives, Jacob, and Payeras, 2018).

One of the most common inventory controls in hotels is length of stay. A minimum length of stay restriction dictates how many nights a person checking in on the night that has this restriction must stay. Length of stay impacts the profitability as hotel labor and supply costs diminish with the increasing length of stay (Kreeger and Smith, 2017; Tranter et al., 2014). A minimum length-of-stay control is often used to accept only stays over a certain duration (Talluri and van Ryzin, 2005). Cancellations and no-shows constitute a threat to the accommodation provider's revenue. Therefore, certain cancellation policies serve as tools to discourage guests from cancelling and to prevent revenue loss. Dynamic pricing refers to the practice of price differentiation according to different criteria – day of the week, events, seasonality, early or late booking – which seek revenue maximization (Vives et al., 2018).

The studies available so far confirmed different behavior patterns between professional/experienced and non-professional/inexperienced hosts. Li, Moreno, and Zhang (2016) conclude that non-professional hosts (who manage only one property) are less likely to offer different rates across stay dates based on the underlying demand patterns, such as those created by major holidays and conventions. Similarly, Wu (2016) found that prices for hosts managing one property showed lower dispersion than for those who manage more than one property. The findings from Gibbs et al. (2018) about superhosts versus non-superhosts show variation in pricing across these two types of hosts; moreover, hosts who manage multiple properties vary their prices more than hosts who manage only one property. Kreeger and Smith (2017) conclude that although traditional hotel revenue managers have used minimum length of stay controls for a long time to maximize revenues and control cost – especially during high-demand periods – P2P hosts do not appear to fully utilize RM tools such as minimum length of stay controls. The research conducted by Koh, Belarmino, and Kim (2020) revealed that there are significant differences in RM practices by host characteristics (multi-unit hosts vs. single-unit hosts; superhosts vs. non-superhosts) for three RM tactics: dynamic pricing, minimum stay period, and restricted cancellation. Based on the previous discussion and future research recommendations the main research question for this study became: How the professionalism of P2P accommodation providers' (hosts) relates to their use of RM practices?

As in the previous research (Chen and Xie, 2017; Gibbs et al., 2018; Koh et al., 2020; Kwok and Xie, 2019; Oskam, van der Rest, and Telkamp, 2018), I considered two indicators of hosts' professionalism (independent variables), namely the number of managed properties (single-unit hosts and multi-unit hosts) and the possession of superhost status (superhosts and non-superhosts). Three RM practices (dependent variables) were examined in relation to hosts' characteristics: cancellation policy strictness, minimum stay restriction, and dynamic pricing. Based on previous studies, the research hypotheses were set in such a way that the more professional the host, the more actively they applied RM practices.

Dependent variables		Hypotheses / Independent variables	Multi-unit hosts	Super-hosts
Cancellation policy	H1a	Properties managed by multi-unit hosts have a stricter cancellation policy than properties managed by single-unit hosts.	X	
	H1b	Properties managed by superhosts have a stricter cancellation policy than properties managed by non-superhosts.		X
Minimum stay	H2a	Properties managed by multi-unit hosts have more days of minimum stay than properties managed by single-unit hosts.	X	
	H2b	Properties managed by superhosts have more days of minimum stay than properties managed by non-superhosts.		X
Dynamic pricing	H3a	Properties managed by multi-unit hosts have more aggressive dynamic pricing than properties managed by single-unit hosts.	X	
	H3b	Properties managed by superhosts have more aggressive dynamic pricing than properties managed by non-superhosts.		X

Source: own elaboration.

Methodology

Data

This study analyzed property-level monthly pricing records and chosen characteristics of properties offered for short-term tenancy through Airbnb service in Krakow and Warsaw, Poland. These two cities are the two locations with the highest number of

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properties available through Airbnb in Poland, responsible for almost 38% of all historical Airbnb listings in the country. The study used property-level data for three RM practices: cancellation policy, minimum stay, and dynamic pricing, along with information regarding hosts' characteristics: the number of properties offered per host and the possession of superhost status.

The initial dataset comprised 497,083 records of property-level monthly pricing records for 40,268 properties in the period of 67 months since the beginning of data availability for Poland until the day of the study (August 2015 – February 2021). Several limitations were applied when sharpening the dataset for the main analysis, which I describe in detail below.

The data for this research were obtained from AirDNA company, the world's leading provider of short-term vacation rental data and analytics, which tracks the daily performance of over 10 million listings in 120,000 markets globally on Airbnb, Vrbo, and more (AirDNA, 2021). The AirDNA data were used in the previous studies regarding P2P accommodation (Chen and Xie, 2017; Gibbs et al., 2018; Koh et al., 2020; Kwok and Xie, 2019).

Variables

In this study, the three RM practices applied for properties offered through Airbnb service in Poland were dependent variables: cancellation policy, minimum stay, and dynamic pricing.

Cancellation policy is a combination of certain rules applied in case the guest wants to cancel the reservation; the policy is posted by the host online for each property separately. In Airbnb service, several pre-defined cancellation policies are used, which combine certain cancellation periods and refund terms (Airbnb, 2021a). The *flexible* policy is the most adaptable option, which allows guests to freely cancel until 24 hours before check-in; if cancelled before check-in, the guest receives a full refund minus the first night and service fee. The *moderate* policy allows for free cancellation five days before check-in; if cancelled before check-in, the guest receives a 50% refund minus the first night and service fee. The *strict* policy fully refunds the nightly rate if the guest cancels within 48 hours of booking and at least 14 full days prior to the listing's local check-in time; afterward, guests can cancel up to seven days before check-in and receive a 50% refund of the nightly rate and the cleaning fee but not the service fee. On top of the three main cancellation policies, there are also two *superstrict* policies (30 and 60 days) available only to software-connected hosts. They assume, that for a 50% refund of the nightly rate, the guest must cancel 30 (or 60 respectively) full days before the listing's local check-in time. Afterward, the nights not spent are not refunded. In this study, the cancellation policy variable was developed as an ordinal variable. The most recent information available for each property was used. As *super-strict* policies were only applied to 0.2% of properties, it was merged with the *strict* policy, leading to three levels: flexible = 0, moderate = 1, and strict = 2. Other authors define this variable similarly as either three-level (Chen and Xie, 2017) or four-level (Koh et al., 2020) ordinal type variable.

Similarly to cancellation policy, minimum stay is the online information posted by the host for each property separately, which states what is the minimum number of nights for which the property may be rented. This study used the most recent information available for each property. In the analyzed dataset, this variable ranged from 1 to 690. As properties with the minimum stay longer than 31 nights constituted less than 0.6% of properties – and the study was focused on short-term tenancy properties – the range of this variable was limited to 1–31 days; previous research applied similar limitations (see Koh et al., 2020). In contrast, 58.7% of the properties applied a one-day minimum stay length, so the binary variable was developed by taking values of 0 for properties with a one-day minimum stay length and 1 for the properties with more than a one-day minimum stay length restriction. In practice, this distinguished the properties with no minimum stay restriction length (one day) from the properties that set any minimum stay restriction length (more than one day).

To define dynamic pricing use, the records were first limited only to those properties, with the pricing history of minimum four months available. This step was necessary to properly detect seasonal dynamic pricing patterns. This action narrowed the number of properties from 40,268 to 26,080 and showed that ca. 35% of the studied properties had a life cycle of less than four months. A similar phenomenon of properties' short life cycle was revealed by Koh et al. (2020). To enable comparisons among the properties, the relative standard deviation (RSD) was calculated for all the properties, while dynamic pricing variable was defined with RSD ranging from 0% to 212% and interpreted as how aggressive dynamic pricing was applied for a given property: the higher the RSD, the more aggressive the dynamic pricing. The RSD is commonly used in time series data analysis and as a measure of price dispersion (see Gibbs et al., 2018). However, as the RSD in the analyzed dataset assumed values above 100% only for 0.3% of properties and the investigation of data suggested other than dynamic pricing reasons (e.g. property refurbishment or upgrade), I limited the variable to values from 0% to 100% and defined it as a ratio variable.

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After applying the above limitations on minimum stay and dynamic pricing variables, the final dataset comprised of 479,282 pricing records for 25,827 properties.

To verify the main research question – how would the professionalism of P2P hosts affect their use of RM practices? – I used two hosts' characteristics as independent variables: managing one or many properties (single-unit host vs multi-unit host) and possessing a superhost status (non-superhost vs superhost).

As already described in the literature (Koh et al., 2020; Kwok and Xie, 2019), there are differences in motivations between the hosts who manage only one property or many. The single-unit hosts' motivations toward P2P accommodation are more social and emotional, while multi-unit hosts apply more importance to economic motivations and profit maximization. As proposed in previous research – via matching host IDs and property IDs – this study identified hosts with more than one property ID as multi-unit hosts and assigned them with 1 while the hosts with only one property ID as single-unit hosts and assigned them with 0. Therefore, a binary variable was developed that indicated multi-unit and single-unit hosts groups.

As for the superhost variable, there are four criteria to become a superhost in Airbnb service (Airbnb, 2021b). First, superhosts must have a 4.8 or higher average overall rating based on reviews from their Airbnb guests in the past year; the maximum available rating is 5.0. Second, superhosts have completed at least 10 stays in the past year or 100 nights over at least three completed stays. Third, superhosts cancel less than 1% of the time, excluding extenuating circumstances. Final criterion is linked to the response rate: superhosts respond to 90% of new messages within 24 hours. Although there is no minimum tenure to become a superhost, all the criteria should be met by the assessment period, which happens every three months, and takes the last twelve months under performance review. Similarly to cancellation policy and minimum stay variables, I used the most recent information available for each property to distinguish superhosts from non-superhosts. The superhost variable was developed as a binary variable, with 0 assigned to non-superhosts and 1 assigned to superhosts.

Method

RM practices were tested against properties' hosts characteristics (both binary variables) in pairs. As cancellation policy was an ordinal variable with three levels and minimum stay was a binary variable, 2x3 and 2x2 contingency tables were used respectively, followed by the chi-square test for independence, phi, Cramér's V, and contingency coefficient analysis. With dynamic pricing variable – which was a ratio variable that proved not to be normally distributed – I performed the Mann–Whitney U test. The SPSS Statistics program was used for all tests calculations. The general model for all pairs of variables was as follows:

$$\mathrm{RM} = a_0 + a_1\,\mathrm{Host} + e,$$

in which RM represented one of the RM practices applied to a given property (cancellation policy, minimum stay, or dynamic pricing), Host represented a given property's host characteristics (multi-unit host or superhost), a_0 represented a constant, a_1 represented a coefficient, and e represented random error.

Results

The data in this study covered 25,827 properties ran by 9714 hosts. Table 1 shows that multi-unit hosts – who accounted for 31.7% of all studied hosts – were responsible for 74.3% of properties. Compared to previous research, these results were higher for both indicators. Kwok and Xie (2019) reported that multi-unit hosts accounted for almost 16% of hosts and were responsible for 40% of the properties, while Li et al. (2016) reported it was 18% and 24% respectively. The highest property percentage was reported by Koh et al. (2020): 50.2% of properties in their study were ran by multi-unit hosts. These discrepancies might come from the fact that the current study was based on very recent data (until 2021), while the previous datasets concerned the years 2014–2018, which may indicate the further intensification of hosts' professionalization process.

Table 1. Multi-unit host, superhost property characteristics and hosts split.

	PROPERTIES						HOSTS					
	NSH		SH		Total		NSH		SH		Total	
SUH	5430	**21.0%**	1203	**4.7%**	6633	**25.7%**	5430	55.9%	1203	12.4%	6633	**68.3%**
MUH	14,973	**58.0%**	4221	**16.3%**	19,194	**74.3%**	2309	23.8%	772	7.9%	3081	**31.7%**
Total	**20,403**	**79.0%**	**5424**	**21.0%**	**25,827**	**100.0%**	**7739**	**79.7%**	**1975**	**20.3%**	**9714**	**100,0%**

Note: SUH – single-unit host, MUH – multi-unit host, NSH – non-superhost, SH – superhost.
Source: own elaboration of AirDNA (DOA: March 2021).

In terms of properties characteristics, the biggest group – accounting for 58.0% – were properties managed by multi-unit hosts who were not superhosts. However, when it comes to hosts characteristics, the biggest group (55.9%) were single-unit hosts who were not superhosts.

The data in this study covered two biggest cities in Poland, Warsaw and Krakow. The basic information on data spread by property location is shown in Table 2. The data were distributed proportionally, both the number of monthly pricing records and the number of properties were slightly higher for Krakow: 53.4% of monthly pricing data and 51.7% of properties analyzed were located in Krakow.

Table 2. The cities and data used in the study

City	No. of monthly pricing data		No. of properties	
Krakow	255,853	53.4%	13,348	51.7%
Warsaw	223,429	46.6%	12,479	48.3%
Total	**479,282**	**100.0%**	**25,827**	**100.0%**

Source: own elaboration of AirDNA (DOA: March 2021).

The two studied cities differ in terms of multi-unit host and superhost characteristics: 81.0 % of properties in Krakow and 73.9% of properties in Warsaw were managed by multi-unit hosts; 23.1% of properties in Krakow were managed by superhosts, while in Warsaw it was only 18.8%. Table 3 shows the details of hosts' characteristics by city. The biggest difference between the cities was visible in terms of the proportion of properties managed by single-unit hosts who were not superhosts: it was 15.3% of all properties available in Krakow and 21.5% in Warsaw. This difference was compensated by the properties managed by multi-unit hosts who were superhosts: 19.3% of all properties available in Krakow and 14.2% in Warsaw. These results would suggest the higher professionalization of hosts operating in Krakow for both criteria: managing one or more properties and possessing a superhost status.

Revenue management practices by city details are shown in Table 4. As for cancellation policy, the biggest proportion of properties was offered with the flexible policy (40.0% for Krakow and 44.2% for Warsaw), followed by moderate policy (33.4% of properties). The least frequently used cancellation policy was the strict policy applied to 26.6% of properties in Krakow and 22.3% of properties in Warsaw. When it comes to the minimum stay variable, 57% of properties in Krakow applied the one-day minimum stay restriction, while for Warsaw this was 60.4%.

Table 3. Multi-unit host and superhost property characteristics by city

		Non-superhosts		Superhosts		Total	
Krakow	Single-unit hosts	2039	15.3%	502	3.8%	2541	19.0%
	Multi-unit hosts	8231	61.7%	2576	19.3%	10,807	81.0%
	Subtotal	**10,270**	**76.9%**	**3078**	**23.1%**	**13,348**	**100.0%**
Warsaw	Single-unit hosts	2679	21.5%	574	4.6%	3253	26.1%
	Multi-unit hosts	7454	59.7%	1772	14.2%	9226	73.9%
	Subtotal	**10,133**	**81.2%**	**2346**	**18.8%**	**12,479**	**100.0%**
Total	Single-unit hosts	4718	18.3%	1076	4.2%	5794	22.4%
	Multi-unit hosts	15,685	60.7%	4348	16.8%	20,033	77.6%
	Total	**20,403**	**79.0%**	**5424**	**21.0%**	**25,827**	**100.0%**

Source: own elaboration of AirDNA (DOA: March 2021).

Table 4. Revenue management practices by city

		Krakow		Warsaw	
Cancellation policy	Flexible	5335	**40.0%**	5517	**44.2%**
	Moderate	4457	**33.4%**	4178	**33.5%**
	Strict	3556	**26.6%**	2784	**22.3%**
Minimum stay	1-day	7614	**57.0%**	7538	**60.4%**
	> 1-day	5734	**43.0%**	4941	**39.6%**
Dynamic pricing	0–5%	1166	**8.7%**	1801	**14.4%**
	5–10%	1657	**12.4%**	2792	**22.4%**
	10–15%	2602	**19.5%**	2739	**21.9%**
	>15%	7923	**59.4%**	5147	**41.2%**

Source: own elaboration of AirDNA (DOA: March 2021).

Moreover, Table 4 above shows the details for dynamic pricing variable distribution by 5pp. intervals. The Warsaw vs. Krakow distribution shows more properties in the first three intervals covering the values of 0–15% – with 58.8% of properties for Warsaw vs. 40.6% for Krakow – which suggests that Warsaw properties hosts applied less aggressive dynamic pricing than Krakow properties hosts.

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The basic descriptive analysis of the variables is shown in Table 5. Superhosts managed 21.0% of all properties, which in comparison to previously reported studies, is a relatively high number. Chen and Xie (2017) reported 14% of properties to be managed by superhosts and Koh et al. (2020) – only 9.6%. It might be another sign of P2P hosts professionalization as well as the superhost badge system getting more attention and popularity.

Table 5. Variables' summary and basic description

Variable	Type	Description	N	Mean	Std. Dev.
Multi-unit host	Binary	Single-unit host = 0; Multi-unit host = 1	25,827	0.7432	0.4369
Superhost	Binary	Non-superhost = 0; Superhost = 1	25,827	0.2100	0.4073
Cancellation policy	Ordinal	Flexible = 0; Moderate = 1; Strict = 2	25,827	0.8253	0.7970
Minimum stay	Binary	1-day = 0; >1-day = 1	25,827	0.4133	0.4924
Dynamic pricing	Ratio	[0;1]; distribution: not normal	25,827	0.1837	0.1485

Source: own elaboration of AirDNA (DOA: March 2021).

The majority of properties employed flexible or moderate cancellation policy (mean: 0.825). In comparison to earlier research concerning this RM practice, the result was somewhat lower: the means reported by Chen and Xie (2017) and Koh et al. (2020) were falling between moderate and strict policies, which suggests that a less flexible policy was most popular in their samples.

As for the minimum stay restriction, one-day minimum stay was applied in 41.3% of properties. This finding was almost in line with previous research, as Koh et al. (2020) reported 43% of the properties using a one-day minimum stay.

In the case of the dynamic pricing variable, 18.37% of pricing fluctuations from the mean were observed. This variable was difficult to compare with previous research, as I observed some discrepancies in variable operationalization, such as different exclusion rules, monthly vs. daily data, binary vs. ratio variable definition, and standard deviation vs. relative standard deviation. For this variable the results in relation to hosts' characteristics are more comparable.

Hypotheses H1a and H1b refer to cancellation policy applied for properties managed by multi-unit hosts and superhosts respectively: a stricter cancellation policy was to be applied to properties ran by multi-unit hosts or superhosts compared to properties managed by single-unit hosts or non-superhosts. For both hypotheses, the Pearson's chi-squared test indicated there was a significant positive relationship between cancellation policy and multi-unit hosting (Pearson's $\chi^2 = 98.959$, $p < 0.001$) or the superhost characteristics of a property (Pearson's $\chi^2 = 78.513$, $p < 0.001$). As we may see in Table 6 above, multi-unit hosts applied strict cancellation policy in 26.1% and flexible policy in 40.8% of properties, while single-unit hosts applied strict cancellation policy only in 20.2% and flexible policy in 45.6% of properties. For superhost variable, the discrepancies between the groups were mostly visible in the application of flexible vs. moderate policies (Table 6), as flexible cancellation policy was used in 37.8% of properties ran by superhosts and in 43.1% of properties managed by non-superhosts. Thus, the results confirm hypotheses H1a and H1b.

Table 6. Revenue management practices by host characteristics

		Single-unit hosts		Multi-unit hosts		Non-superhosts		Superhosts	
Cancellation policy	Flexible	3027	**45.6%**	7825	**40.8%**	8803	**43.1%**	2049	**37.8%**
	Moderate	2268	**34.2%**	6367	**33.2%**	6559	**32.1%**	2076	**38.3%**
	Strict	1338	**20.2%**	5002	**26.1%**	5041	**24.7%**	1299	**23.9%**
Minimum stay	1-day	2873	**43.3%**	12,279	**64.0%**	12,314	**60.4%**	2838	**52.3%**
	> 1-day	3760	**56.7%**	6915	**36.0%**	8089	**39.6%**	2586	**47.7%**
Dynamic pricing	0%–5%	1348	**20.3%**	1619	**8.4%**	2646	**13.0%**	321	**5.9%**
	5%–10%	1536	**23.2%**	2913	**15.2%**	3491	**17.1%**	958	**17.7%**
	10%–15%	1388	**20.9%**	3953	**20.6%**	4037	**19.8%**	1304	**24.0%**
	> 15%	2361	**35.6%**	10,709	**55.8%**	10,229	**50.1%**	2841	**52.4%**

Source: own elaboration of AirDNA (DOA: March 2021).

Hypotheses H2a and H2b referred to the minimum stay restriction applied for properties managed by multi-unit hosts and superhosts: more days of minimum stay restriction was to be applied to properties ran by multi-unit hosts or superhosts compared to properties managed by single-unit hosts or non-superhosts. For both hypotheses, the Pearson's chi-squared test indicated there was a significant relationship between minimum stay and multi-unit (Pearson's $\chi^2 = 867.653$, $p < 0.001$) or superhost characteristics of the property (Pearson's $\chi^2 = 113.966$, $p < 0.001$), but in the case of multi-unit hosts the relation appeared to be negative (Phi = -0.1830). Table 6 above clearly shows that the one-day minimum stay was applied to 64.0% of properties ran by multi-unit

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hots and only to 43.3% of properties managed by single-unit hosts. Both results did not support the hypothesis H2a. Moreover, the results did not support the results of previous research. This might be explained by the multi-unit hosts striving for competitiveness and high occupation rates, which shows their high flexibility and ability to effectively handle the complexity resulting from the one-day minimum stay restriction application. Furthermore, this makes their offer even more competitive to that of hotels. Results in Table 6 above confirmed the positive relationship between minimum stay and superhost position, as the one-day minimum stay restriction was used for 52.3% of properties managed by superhosts, while for properties ran by non-superhosts the one-day minimum stay was applied to 60.4% of properties. This supported the hypothesis H2b.

Table 7. Chi-squared and Mann–Whitney U tests

		Multi-unit host		Superhost	
Cancellation policy	Pearson's chi-squared	**98.959**	*p < 0.001*	**78.513**	*p < 0.001*
	Phi	**0.0619**	*p < 0.001*	**0.0551**	*p < 0.001*
	Cramer's V	**0.0619**	*p < 0.001*	**0.0551**	*p < 0.001*
		0 cells (0.0%) have expected count less than 5			
Minimum stay	Pearson's chi-squared	**867.653**	*p < 0.001*	**113.966**	*p < 0.001*
	Phi	**-0.1830**	*p < 0.001*	**0.0664**	*p < 0.001*
	Cramer's V	**0.1830**	*p < 0.001*	**0.0664**	*p < 0.001*
		0 cells (0.0%) have expected count less than 5			
Dynamic Pricing	Mann–Whitney U	**80,533,147**	*p < 0.001*	**57,558,612**	*p < 0.001*
	Standardized test statistics	**32.24**		**4.56**	
		SUH	**MUH**	**NSH**	**SH**
	Mean ranks	**10,369.71**	**13,793.25**	**12,804.91**	**13,324.34**

Note: SUH – single-unit host, MUH – multi-unit host, NSH – non-superhost, SH – superhost.

Source: own elaboration of AirDNA (DOA: March 2021).

Hypotheses H3a and H3b referred to another RM practice, namely dynamic pricing: more aggressive dynamic pricing was to be applied to properties managed by multi-unit hosts and superhosts compared to those ran by single-unit hosts and non-superhosts. The Mann–Whitney U test (Table 7 above) estimated a significant positive relation for multi-unit hosts (standardized test statistics = 32.24, $p < 0.001$) and superhosts (standardized test statistics = 4.56, $p < 0.001$). Mean ranks showed stronger differences for multi – vs. single-unit hosts than for superhosts vs. non-superhosts. The results in Table 6 above confirmed these findings, as pricing fluctuations from 0% to 10% were noticed for only 23.6% of properties ran by multi-unit hosts, while for properties managed by single-unit hosts it was 43.5%. Furthermore, I noticed more than 15% price fluctuation for 55.8% of properties ran by multi-unit hosts while only for 35.6% of properties managed by single-unit hosts in which such an aggressive dynamic pricing was applied. Moreover, less than 5% pricing fluctuations were observed for 5.9% of properties ran by superhosts, while 13.0% for non-superhosts. Both results supported hypotheses H3a and H3b.

Notably, the statistical significance of these relations is partly driven by the very large sample size, and the estimated relations are not particularly strong, which agrees with previous research (Gibbs et al., 2018; Koh et al., 2020).

Discussion, Limitations, and Future Research

In summary this study adds to the existing research by offering the analysis of longitudinal and very recent data, covering professional vs. non-professional P2P hosts' behaviors in terms of three RM practices in Central-Eastern Europe settings by scrutinizing the research gaps indicated by previous studies.

The study clearly showed the further growth of P2P hosts' professionalization: significantly higher percentages of properties were ran by multi-unit and superhosts compared to previous studies. This might have stemmed from the fact that the analyzed data was very recent (until 2021, while previous studies covered datasets until 2018) or due to some specificities of the Polish settings.

Moreover, the study proved that professional and non-professional hosts' behaviors differ in RM practices application. Multi-unit hosts and superhosts less often used flexible cancellation policy compared to single-unit hosts and non-superhosts respectively, while the former generally applied stricter cancellation policies for the properties they managed. Moreover, multi-unit hosts and superhosts applied more aggressive dynamic pricing compared to their counterparts, but the group differences were much smaller in the case of superhosts/non-superhosts clusters. The surprising negative relation of multi-unit host to minimum stay variable emerged as an interesting phenomenon that does not support previous studies' results. This might be explained by the multi-unit hosts striving more for competitiveness and high occupation rates, thus

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showing their high flexibility and ability to effectively handle complexity resulting from the application of one-day minimum stay restriction. Furthermore, this makes their offer even more competitive than that of hotels: on top of P2P accommodations being larger, better located, less artificial, and providing more privacy, they also match the restrictions on the minimum length of stay.

The two indicators for hosts' professionalism selected for this study proved to differ in their characteristics. While multi-unit hosts' behaviors showed distinctive differences compared to single-unit hosts – revealing the former's strong pursuit of revenue and competitiveness growth – the superhosts showed less discrepancies against non-superhosts, which might serve as an indicator of the former's goals being less economically driven. Superhosts seem to be more focused on the quality of service and customer experience, which results in higher overall ratings from guests, which might not necessarily go in line with hard economic objectives driven by the RM approach.

The practical implications of this study suggest that there are two groups that can benefit from it: P2P accommodation hosts and hoteliers. As offering different prices across stay dates results in higher occupancy rates and revenues (Li et al., 2016), this study revealed the revenue potential for the hosts who underutilized dynamic pricing, namely single-unit hosts. For hoteliers, this study should serve as a warning of P2P hosts' professionalization, as the latter are gradually becoming equal competitors of hotels. The finding that brought considerably different result than previous studies was the negative relation between multi-unit host and minimum stay; this might be yet another argument for the multi-unit hosts professionalization, as they are prepared to prioritize flexibility over complexity.

The limitation of this research is that it only covered two cities in Poland. Nevertheless, this agrees with previous studies, also concentrated on big cities, in the USA or Canada, and allows for direct comparisons of results. Although the two locations were responsible for almost 38% of all historical Airbnb listings in Poland and represented some discrepancies regarding the business – (Warsaw) or tourist-orientation (Krakow) of the locations, my study might miss some *big city* vs. *holiday destination* trends, especially in view of seasonal price differentiation, minimum stay restriction, or multi-unit host patterns. Therefore, future research should include holiday destinations like seaside or ski resorts.

Another limitation is that this study captured the dynamics of the pricing variable, while capturing only a snapshot of latest data available for other variables. Therefore, future research should consider scrutinizing how other RM practices evolved in time.

As the data covered the period until February 2021, the analysis illustrated the differences in RM practices, including hosts' reactions to the Covid-19 pandemic. However, as the Covid-19 pandemic constituted a major disruption to the hospitality industry, I recommend a separate detailed analysis of this issue.

Moreover, this study focused on the relations between the hosts' professionalism and RM practices. However, there are other variables related to the implementation of RM practices in P2P accommodation, such as property location or type, occupancy rate, or total revenue, which could serve as useful future research extensions of this study.

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