Player Analytic Technologies in Tennis: An Investigation of Non-professional Players' Personal Values and Perceptual Orientations

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Abstract. The use of technology in sports has grown significantly in recent years. Analytic systems, in particular, have changed the way athletes train, execute and evaluate their performance. In tennis, however, the cost for installing, maintaining and operating such systems has so far prevented greater market penetration. While more affordable devices are emerging, their acceptance and consequent adoption remains low, although players and coaches understand their value and usefulness. Exploring hindering factors, the goal of the research presented in this paper was to better understand existing users, so as to identify those device features, which directly link to personal values and hence may be seen as most important for increasing adoption. Interviews with 20 amateur tennis players showed that the video feature seems to be most essential, as it helps players improve their game and consequently increase their competitiveness. Furthermore, they seem strongly interested in the systems' statistics and ranking functions.

Keywords: Player analytics technology · Means-end-chain theory
Value perception

1 Introduction

Throughout the last decade, the sports industry has experienced significant adaptations. The introduction of sport analytic systems has changed the way in which coaches and players analyze, understand and control performance growth. In tennis, however, this technological revolution has so far mainly focused on professionals and not so much on upcoming high performance junior or recreational players. In order to better understand potential success factors our research therefore focused on current users of such systems. That is, we used an interview study and consequent content analysis to identify personal values attributed to a distinct player analytic technology. From a hardware point of view, the focus

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was set on the *PlaySight SmartCourt*[1], as this seems to be the system with the largest number of features currently on the market. In order to identify users' personal values, we first identified relevant system attributes and then focused on understanding their consequences. Once attributes and consequence had been identified, the goal was to dig deeper and make users share their personal values, i.e. identify the goals motivating their system usage. These three elements, i.e. *attributes*, *consequences* and *values*, were identified using the Means-End Chains (MEC) theory [1].

2 Theory of Means-End Chains

MEC theory is based on the hypothesis that users/consumers of a product see the product and its attributes as a tool to accomplish a desired end-state. The theory states that consumers' product selections are linked to a hierarchical model composed of a product's *attributes*, the *consequences* of its use and the *personal values* attached to their product selection [2]. A chain is thus composed of three hierarchical levels linking *attributes* with *consequences* and *values.* The higher the level, the higher its abstraction [3]. The two lower levels (i.e. *attributes* and *consequences*) are concerned with the users' knowledge of a product's attributes and/or characteristics and the consequences linked to them. The highest, most abstract level (i.e. *values*) locates the personal values associated with using the system [4]. Thus, a ladder or chain reaching from *attributes* to *values* displays an individual's perceptual orientation towards a product, which helps identify the psychological consequences of product use and consequently relates to a user's personal values [5].

3 Research Methodology

We conducted a total of 20 interviews with amateur tennis players who use the *PlaySight SmartCourt* at least 2 times per week. The goal was to identify the relevant emotional triggers (i.e values) that motivate the utilization of this system. Following the above described MEC theory, the collected interview material was investigated using a laddering technique composed of the following five stages: (1) laddering, (2) coding, (3) development of an Implication Matrix, (4) development of a Hierarchical Value Map, and (5) identification of dominant perceptual orientations [2].

3.1 Laddering, Coding and Implication Matrix

We started with one-on-one interviews, aimed at understanding how users translate features into meaningful relations between themselves and the system. Here the focus was set on the *"Why is that so important for you?"* question. The goal

[1] https://www.playsight.com/.

was to identify a perceived link between the system's attributes and users' associated personal values. Next, these links were coded, i.e. categorized into *attributes*, *consequences* and *values*. The following Implication Matrix (IM) then composed a square matrix of these elements, listing codes in both rows and columns and forming interaction points between elements. Connections are illustrated in fractional form, where the left part of the decimal (the part preceding the comma) shows direct connections and the right part of the decimal (the part following the comma) shows indirect connections [6] (Note: A connection between elements is considered direct when they are next to each other, and indirect when the two elements are part of the same chain but not consecutively aligned [2]).

3.2 Hierarchical Value Map and Dominant Perceptual Orientations

The Hierarchical Value Map (HVM) seeks to visually represent the meaningful connections of the IM by focusing on those connections which fulfill a given cut-off criterion. In cases where the sample consists of 50 ore less participants a cut-off criterion of 3–5 connections is recommended [2]. The HVM further differentiates between five different types of relations:

- A → D: adjacent elements with a high number of direct connections.
- N → D: non-adjacent elements with a high number of direct connections.
- A → I: adjacent elements with a high number of indirect but low number of direct connections.
- N → I: non-adjacent elements with a low, non-zero number of direct but a high number of indirect connections.
- N → O: non-adjacent elements with a low (or zero) number of indirect connections.

The A → D relationships are the most important ones, signifying the base of the map. These relations are most common as they represent the strongest ties. The N → D relations are not very common, as most elements that have a lot of direct relations are mapped as adjacent. Nevertheless, in some cases an element may fit between two other elements and in doing so may even give a distinct meaning to this relation. The A → I relations appear usually when no dominant path is visible and two elements are mapped based on their indirect relation rather than their direct one. The N → I relations are also common as many of the elements which have indirect relations are found in chains that have a high number of repetitions. As a consequence, the strong ties or direct relations become dominant and are the ones mapped adjacently. Finally the N → O relation, which is the least common, refers to elements which are part of the same chain in the map but were never explicitly highlighted by a participant. This may occur when one consequence is associated with multiple attributes and every attribute is strongly linked to a particular personal value. So even if two elements have zero indirect relations they may be mapped as an N → O relation [2].

4 Discussion of Results

From the 20 interviews we extracted 109 chains; i.e. element relationships in the form of *attribute* → *consequence* → *value*, with a total of 35 unique elements (cf. Fig. 1), all of which were given a number so that they could be identified when building the consequent IM shown in Fig. 2. As already explained earlier, the IM displays the number of direct and indirect relations between different elements. For example, cell (1.12) shows that the attribute *Video* (1) and the consequence *Identify mistakes* (12) have a total of 22 relations of which 19 are direct and 3 are indirect.

Attributes	Consequences	Values
(1) Videos	(12) Identify mistakes	(25) Fun
(2) Statistics	(13) Improve game	(26) Independence
(3) User-friendly	(14) Coach feedback	(27) Efficiency
(4) Information Availability	(15) Save time	(28) Competitive
(5) Ranking	(16) Prepare next game/tournament	(29) Personal Fulfillment
(6) 3D Function	(17) Compare with other players	(30) Ambition
(7) Drill Function	(18) Better understanding	(31) Family
(8) Auto-tagging Function	(19) Better chances of winning	(32) Perfectionist
(9) Visualization Function	(20) Learn	(33) Responsibility
(10) Video Speed/Zoom Function	(21) No excuses	(34) Confidence
(11) Social Function	(22) Extra Motivation	(35) Health
	(23) See Your Progress	
	(24) Recognition	

Fig. 1. The 35 unique elements (i.e. attributes, consequences and values) extracted from 20 interviews.

In order to identify the most important element connections, the subsequent HVM includes only those relationships, which show at least tree links. It was further decided to only consider direct links, as such puts the focus on strong ties. Applying these two criteria the data was reduced by approximately one third. The resulting HVM is presented in Fig. 3.

4.1 General Findings

The first main conclusion that can be drawn from both the IM and the HVM is that the majority of attributes share the same consequence, i.e. they help *Identify mistakes* (12) in the game of players. The attributes *Auto-tagging* (8), *Video* (1), *Statistics* (2), *3D function* (6) and *Drill function* (7) are all A → D relations, with the consequence element *Identify mistakes* (12). Particularly dominant, given their high frequency, seem the row-column pairs 1 → 12, 2 → 12 and 1 → 10. The pair 1 → 12 alone shows a total number of 22 (19 direct and 3 indirect) links. Another important aspect highlighted by the HVM is the strong connection between the *Identify mistakes* element (12) and the *Improve game element* (13), with a total frequency of 51 connections (45 direct and 6 indirect).

	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35
1	19.03	2.18	2.04		0.02			0.08	2.01	2.01				0.04			0.07	0.06	0.03		0.02	0.02	0.04	
2	7.01	6.05	0.01					0.08				1.00		0.01	0.01		0.10	0.02					0.01	
3	0.01	0.01		3.01			1.00								1.00	0.04				0.01				
4	2.04	0.06	3.00	4.00	0.02			0.03		1.00					0.01	0.01	0.03	0.02	0.01				0.03	
5						10.00								0.07			0.03		0.01					
6	5.00	2.05			0.01	1.00		0.02									0.05	0.01					0.02	
7	3.00	8.02						0.03			1.00			0.02			0.06	0.01	0.02				0.04	
8	6.01	4.09		2.01			1.01	0.03						0.04		0.01	0.07	0.02	0.02		0.01		0.03	
9	2.00	0.02					2.00	0.01						0.02			0.01	0.01						0.01
10	9.02	0.10	1.00				1.00	0.03	0.01								0.08	0.02	0.01				0.02	
11													1.00										0.01	
12		45.06	2.02		3.00		1.00	1.12	2.00	1.00				0.08	2.00	1.00	1.26	0.14	0.07		0.01		3.11	1.00
13	3.00		1.01					18.01						3.05		1.01	19.15	15.04	3.06		3.00		8.02	
14	2.00	3.02			1.00			0.01									1.01	0.02	1.00	0.02			1.01	
15	3.02	2.03					1.00	0.01							0.01	3.03	1.00	1.00	0.01	0.01	0.01		0.01	
16		2.00	1.00					1.02									0.02	0.01					1.01	
17					1.00									6.01			3.00		1.00				0.01	
18	2.01	2.03		2.00				1.00						0.01		0.01	0.03	0.01			0.01			
19														4.00			14.00	4.00					6.00	
20	1.00	2.02															0.02	0.01	0.01					
21		1.00																0.01				2.00	1.00	
22														1.00										
23																		1.00						
24																							1.00	
25																	1.00	1.00	1.00					
26																								
27																				1.00				
28														4.00					1.00					
29																1.00								
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34																	2.00		3.00					
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Fig. 2. The Implication Matrix built from found element connections.

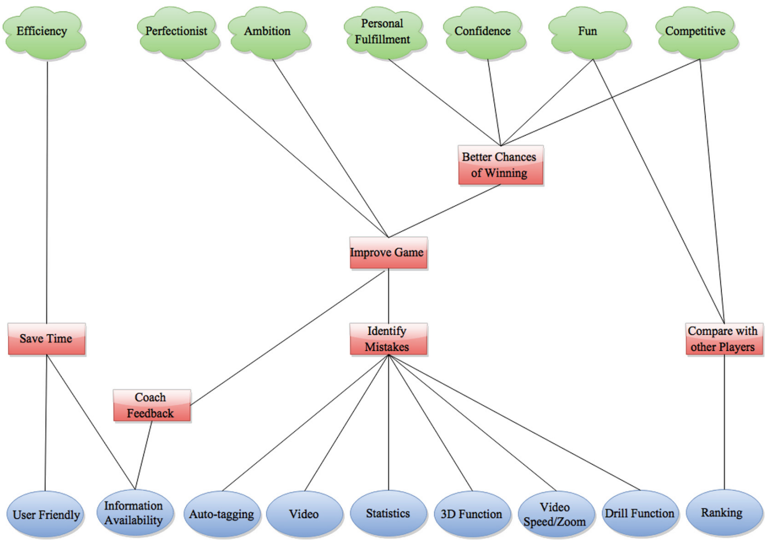

Fig. 3. The Hierarchical Value Map showing element relationships which met the defined threshold.

This shows a clear pattern, underlining that for most participants the consequence of identifying mistakes in their game means to work on them, and by doing so to ultimately improve their *Chances of winning* (19).

The pair 13 → 19 has a frequency of 19 relations, 18 of which are direct. Here it is important to highlight that the pair 13 → 28 is an N → D relation, for even though it shows a high number of direct relations they are mapped as indirect in the HVM (13 → 19 → 28). This is because the element *Better chance of winning* (19) fits between both of these elements and has furthermore a strong connection with the *Competitive* element (28). Also, the *Improve game* element (13), in addition to having an A → D link with the *Chance of winning* element (19), has also links to the elements *Ambition* (30) and *Perfectionist* (32).

Furthermore, is it important to inspect those three attributes which follow a different pathway in the HVM, i.e. *User friendly* (3), *Information availability* (4), and *Ranking* (5) (cf. Fig. 3). The *User friendly* attribute (3) is strongly connected to the *Save time* consequence (15) (although a frequency of 4 is significantly lower than those relation frequencies mentioned earlier). The only other attribute that shares this consequence is the *Information availability* attribute (4). Both of these chains are linked to the personal value *Efficiency* (27).

The *Information availability* element (4) is furthermore a part of the chain 4 → 14 → 13 → 19 → X, where X stands for a number of different elements (i.e. 32, 30, 29, 28, 25 or 34). The main difference between this chain and any of the chains leading to the *Improve game* element (13) is that this one includes the *Coach feedback* consequence (14) instead of the *Identify mistake* one (12). This means that here the link is not to the *Identify mistakes* element (12) but instead to the possibility of receiving feedback from the coach to reach the *Improvement in their game* consequence (13).

Furthermore interesting is that the *Ranking* function (5) is part of a unique chain, which is strongly connected to the *Compare with the other players* element (17). This attribute then conforms two different chains, one ending in *Fun* (25) and the other one ending in *Competitive* (28).

In order to extract more meaningful information from the HVM we will now focus on the most important *attributes*, *consequences* and *values*. Theses elements were determined by comparing the number of relations they were part of.

4.2 Dominant Perceptual Orientations

Any path from bottom (*attribute*) to top (*personal value*) is assumed to be a perceptual orientation [2]. The dominant perceptual orientations are the strongest and consequently most important chains in the HVM. In total we found 46 perceptual orientations. Referring to past studies (cf. [7,8]) we considered two rules in helping us determine the dominant ones. First, we defined a cut-off criterion by considering the mean number of relations (direct and indirect) depicted by all perceptual orientations. Second, such was separately applied to perceptual orientations with three, four and five elements. Doing this we found that in the group of perceptual orientations with three chain elements, only one of the chains seemed dominant. That is, the chain *Ranking* → *Compare with other* *players* → *Fun* was the only one whose value was above the mean. It had a total of 24 relations (16 direct and 8 indirect) which is 33% more than the average of all the other chains in this group.

Concerning the group of perceptual orientations with four elements, a small adaptation in the way those orientations were defined had to be performed so as to increase the accuracy of the results. That is, given that the *Identify mistake* and/or *Improve game* elements were part of more than 90% of all perceptual orientations mapped in the HVM, we decided to exclude their connections to *Information availability* → *Ambition* and *Information availability* → *Perfectionist*. Having applied this adaptation, the average number of relations for this group was 85.08, leading to five perceptual orientations regarded as being particularly strong, of which the one linking the *Video* and the *Ambition* elements (72 direct and 43 indirect relations) was the most dominant one. Important to note here is that four out of the five dominant perceptual orientations led to the *Ambition* value, highlighting its relevance for the user.

Finally, there were 28 perceptual orientations containing five elements. Even if this group had similar issues than the one before, the larger total minimized the effect the *Identify mistake* attribute (12) had on the mean, so that no adaptation was needed. On average a perceptual orientation in this group had 143 relations. A total of 13 of the chains were considered dominant. Here we see that all the chains that started from the *Video* attribute (1) are considered dominant. This is because video, being the core attribute of the system, is linked to more than one personal value. It is also important to highlight that the perceptual orientation *Video* → *Competitive* is the one with the largest number of relations (122 direct and 96 indirect). This is not surprising, considering that in this chain all the core elements are included. Another interesting point may be found in the fact that all the personal values involved in this group of perceptual orientations are in at least one of the dominant perceptual orientations. This speaks for the reliability of the result, as it shows that although the core value (i.e. *Competitive*) is the one which appears most, all of the others were represented in this group as well.

5 Conclusions

In summary, our results show that users perceive the *PlaySight SmartCourt*'s *Video* feature as the most essential one. Other relevant system features include the *Statistics* function, the *Auto-tagging* function, the *Drill* function, the *Video/speed* zoom function, *Information availability*, the *Ranking* function, and the system's overall *User-friendliness*. From a consequence perspective we found that two are perceived as particularly important. That is, the *Identify mistakes* and/or *Improve game* consequences appear in 94% of all identified perceptual orientations. Consequently it may be assumed that users who use an external aid in their tennis sessions do so in order to achieve better results in their game development. Such is also highlighted by the *Better chance of winning* consequence, following all the other core consequences identified in the HVM.

However, the personal values as to why users want to identify their mistakes and improve their game vary (although it is worth noting that a large number of them end in the *Competitive* value). We may therefore argue that the *PlaySight SmartCourt* system (and similar PAT devices) are predominantly used by competitive players who want to improve their game and consequently their performance in competitive events such tournaments. However, a large number of participants also associate the systems' features with values of *Personal fulfillment* and *Fun*. This means players do not only value pure competitive advances (i.e. win over others) but also aim at improving their game as a means of personal fulfillment. Finally, our analysis also showed that people use these systems to increase their *Confidence* - a potential marketing opportunity so far largely overlooked by system providers.

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