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Investigating Transfer Motivation Profiles, Their Antecedents and Transfer of Training

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Abstract: Despite investments of companies in employee trainings, transfer of training remains low. One component influencing transfer is transfer motivation. Recent insights have shown that different components of transfer motivation possibly independently influence transfer of training. It is therefore possible that transfer motivation profiles can be distinguished. However, it is unclear whether such motivational profiles exist. In this study, we investigated motivational profiles, how these profiles differ in antecedents influencing transfer motivation and how these profiles differ in transfer intention and transfer of training. This study does so by using the unified model of task-specific motivation (UMTM). Data were collected among 1317 participants who filled in a questionnaire representing the UMTM components directly after the training and indicated transfer after six weeks. Outcomes showed that four transfer motivation profiles could be distinguished, labeled: 'very optimistic', 'moderately optimistic', 'personal value' and 'conscious'. Moreover, profiles scoring higher on motivational components scored higher on antecedents of transfer motivation, transfer intention and transfer of training. These outcomes suggest that trainings and work circumstances need to be tailored differently toward different trainees to raise their transfer motivation and transfer of training.

Keywords: transfer of training; transfer motivation; transfer intention; latent profile analysis; unified model of task-specific motivation

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1. Introduction

Annually, companies invest heavily in employee training [1,2]. However, the extent to which transfer of training (i.e., the degree to which training content is applied in the work context) [2,3] occurs is often low [2,4]. Previous research has repeatedly identified transfer motivation (i.e., the willingness of employees to apply acquired knowledge, skills and insights in practice) [5] as a positive predictor of transfer of training [2,6,7].

However, several studies [6,8,9] showed that the correlation between transfer motivation and transfer of training differed considerably across studies. As such, the importance of transfer motivation for transfer of training remains unclear. One explanation suggested by Gegenfurtner [10] for this heterogeneity is that transfer motivation often is considered to be one-dimensional [7,11,12], whereas recent research has indicated that transfer motivation includes multiple components that uniquely predict transfer intention and transfer of training [10,13–16]. As such, it seems that not only the amount but also the kind of transfer motivation matters and that transfer motivation should be grounded in contemporary motivational theories [10,15].

In addition, combinations of different kinds of transfer motivation may co-occur differently for different groups of individuals [15]. Individual trainees might differ in terms of combinations of expectations of trainings, reasons to attend trainings and needs during trainings [17]. This possibly has an effect on the amount of transfer that occurs after trainings [18]. However, differences between individuals, such as differences in how different types of transfer motivation co-occur together, are rarely considered within the transfer of training literature. Yet, this might provide an explanation for why transfer occurs more frequently among some individuals than in others. As such, there is a call within the transfer of training literature to conduct more person-centered research (e.g., transfer motivation profiles) in which combinations of different antecedents between individuals are used as explanatory variables [18].

Previous motivation research in the work context suggests that differences exist between groups of individuals in their motivational structure and how these kinds of motivation interact with each other [19,20]. These studies provide evidence that motivational profiles can be derived among employees (see Spurk et al. [21] for an overview) from the perspective of motivational theories such as self-determination theory [22,23] and achievement goal theory [24–26]. To date, only one study [27] has shown that it is also possible to derive specific profiles in which groups of individuals differ in their combinations of different types of transfer motivation.

More research into transfer motivation profiles and their differences in transfer of training can provide insight into whether different groups of trainees may need different support to stimulate transfer motivation and transfer of training. This can inform policy-makers and trainers about how specific trainings and work environments could be tailored to specific groups of trainees. Therefore, this study uses a person-centered approach to investigate profiles of transfer motivation, whether profile membership can be predicted by personal and contextual antecedents that have been found to predict transfer motivation [6,7] and how these groups differ on transfer intention and transfer of training by means of a latent profile analysis (LPA) [cf. 25]. This study carries this out through the lens of the unified model of task-specific motivation (UMTM) [28].

1.1. The Unified Model of Task-Specific Motivation

The UMTM (see Figure 1) (see [28] for an in-depth discussion) integrates six motivation theories, i.e., self-determination theory [29], flow theory [30], expectancy–value theory [31], social cognitive theory [32], theory of planned behavior [33] and person–object theory of interest [34]. Through this integration, the UMTM overcomes two limitations of existing transfer of training frameworks. Firstly, the UMTM takes into account that task-specific motivation is multidimensional by incorporating affective and cognitive types of motivation. Through the integration of the aforementioned motivational theories that each pose a different focus on motivation, the UMTM avoids the necessity of navigating through multiple theories that pose a different and sometimes conflicting focus on motivation [28]. Secondly, unlike existing transfer of training frameworks, e.g., [2,12,35], the UMTM specifies interrelationships between different personal and contextual antecedents and types of motivation in predicting task-specific behavior [28]. In doing so, the UMTM potentially provides more insight into the unique predictive value of the different antecedents of transfer of training.

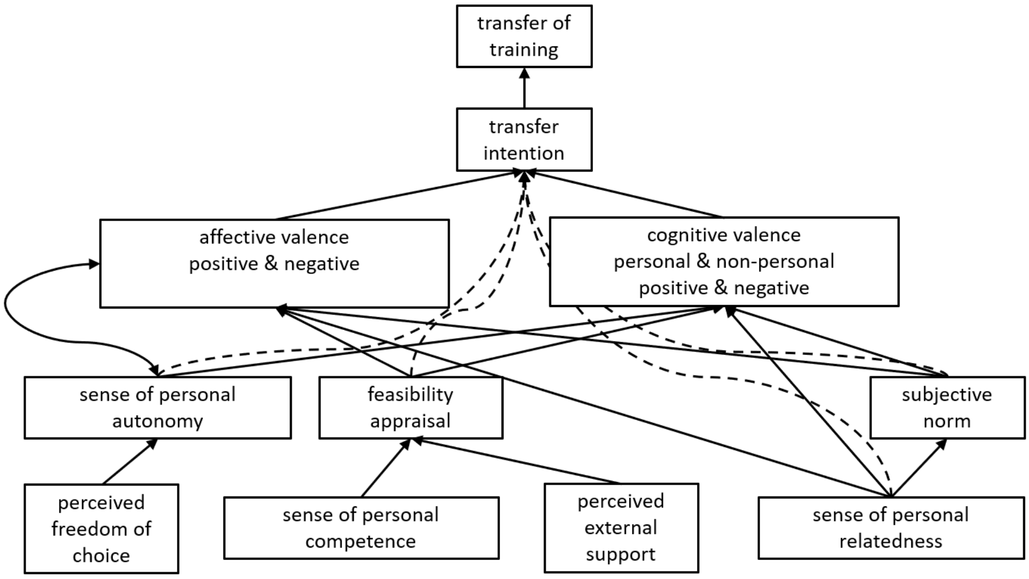


Figure 1. The unified model of task-specific motivation ([28], adapted by De Brabander & Glastra [36,37]). The dashed lines represent direct effects of the UMTM components on readiness for action. These relationships are in line with the theory of planned behavior and previous empirical findings e.g., [36].

Personal and contextual antecedents of task-specific motivation (e.g., transfer motivation) and behavior (e.g., transfer of training) that the UMTM identifies can be linked to factors that have been found to influence transfer of training [6,7,12,38–42]. For example, personal feelings of autonomy translate to sense of personal autonomy in the UMTM, whereas social norms and supervisor support are similar to subjective norm and perceived external support of the UMTM. Moreover, these components align with components in existing transfer of training models, e.g., [2,12,35]. Below, we will introduce and discuss the different UMTM components and how they relate to each other.

The UMTM posits that task-specific behavior (i.e., exerting a relatively specific action option) is predicted by task-specific motivation [28]. This motivation is expected to be multifaceted and represented in the model by affective and cognitive valences. These valences are based on the different affective and cognitive-oriented motivational theories. The affective aspects originate, for example, from flow theory [30] and self-determination theory [29], whereas the cognitive aspects stem for example from expectancy–value theory [31]. Affective and cognitive valences are theorized in the UMTM to function relatively independently from each other and, in interaction, form an overall valence appraisal [28]. Affective valences refer to feelings that individuals anticipate when they perform a task (e.g., feeling enthusiastic about applying training content) [28]. Cognitive valences concern the valuation of the possible consequences of performing a task (e.g., higher work efficiency when training content is being used). Performing a task has consequences for individuals themselves and for others (i.e., colleagues and supervisors). Thus, cognitive valences can be both personal and nonpersonal [28]. Considering performing a task causes individuals to experience positive and negative feelings and to foresee positive and negative consequences for themselves and others. As such, the valences can be positive or negative. If the valences are positive, individuals experience positive feelings when they consider performing the task and anticipate positive consequences for themselves and/or others. The opposite is the case when the valences are negative, leading to approach and avoidance motivation [28,43]. However, affective and cognitive valences can also be positive and negative simultaneously [28]. For example, one can see several positive consequences from exhibiting task-specific behavior but still find it unpleasant.

When affective and cognitive valences are positive, it is expected that readiness for action increases, whereas the opposite is the case when the valences are negative [28]. Readiness for action is conceptualized as the willingness of individuals to perform task-specific behavior [36], of which transfer intention is an example. Action is defined as applying task-specific behavior and is predicted by readiness for action [36]. Transfer of training is an example of action. The assumed relationships between these components corroborates with the transfer of training literature, which indicates that higher-quality transfer motivation positively predicts transfer intention and/or transfer of training [10,13–15].

1.2. Task-Specific Antecedents

The UMTM also integrates antecedents predicting affective and cognitive valence, which also originate from the aforementioned motivational theories [28]. The UMTM distinguishes between personal and contextual antecedents. The first personal antecedent is sense of personal autonomy, which is defined as the extent to which individuals perceive themselves as a source for choosing and performing task-specific behavior. The second personal antecedent is sense of personal relatedness, which is conceptualized as the extent to which one experiences a sense of belonging and connection with other people who participate in the context of task-specific behavior. The third personal antecedent is sense of personal competence, which refers to judgments of individuals regarding the extent to which they perceive themselves capable of performing a task successfully [28].

The first contextual antecedent is perceived freedom of action, which is conceptualized as the extent to which individuals experience freedom to make decisions about selecting and performing task-specific behavior. The second is subjective norm, which refers to the inclination to abide by the agreement or disagreement of significant others about performing the task-specific behavior. The third is perceived external support, which is described as the extent to which individuals experience their environment to support or hamper them in performing task-specific behavior (e.g., sufficient working space, expertise among colleagues) [2,28,44]. Perceived external support and sense of personal competence together form an overall feasibility appraisal, which is defined as the expectations individuals have about the feasibility of performing a task successfully [28].

It is expected that feasibility appraisal, subjective norm and sense of personal relatedness (indirectly) positively predict positive valences and negatively predict negative valences, in line with the self-determination theory, expectancy–value theory, theory of planned behavior and social cognitive theory [29,31–33]. Sense of personal autonomy is expected to have a reciprocal association with affective valence but to predict cognitive valence. Perceived freedom of action is expected to predict sense of personal autonomy, which is in line with the self-determination theory [29]. Finally, sense of personal relatedness is expected to predict subjective norm [28].

1.3. A Person-Centered Approach for Investigating Valence Appraisal

Several studies have provided evidence for the dynamics of the UMTM components and for the predictive value of the UMTM for readiness for action. That is, positive and negative valences predict readiness for action positively and negatively, respectively [36,37,45–49]. In addition, these studies also showed that multiple valences together predicted readiness for action. Particularly, positive affective valence and positive personal and nonpersonal cognitive valence positively predicted readiness for action, whereas negative affective and cognitive valence negatively predicted readiness for action [36,37,45–49]. Finally, there is evidence that the valences can predict both self- and externally reported transfer via readiness for action [46–49]. As such, these outcomes provide evidence for the multidimensionality of transfer motivation and for affective and cognitive types of (transfer) motivation to have different effects on task-specific behavior (e.g., transfer of training), in line with outcomes of the studies of Gegenfurtner [10,14,15].

However, previous studies did not yet investigate the relationships between the different valences for different subgroups. This could be interesting, as this can test the notion of De Brabander and Martens [28] that positive and negative affective and cognitive valence possibly independently predict readiness for action. It is relevant to acquire more insight into this, as this can unveil how possible interactions between affective and cognitive valences might hamper or enhance readiness for action [28] and whether these interactions in transfer motivation function differently for different trainees [15]. Eventually, this can provide us with more insight into explaining the complex phenomenon of (transfer) motivation [28]. Moreover, insights into such motivation groups could provide a better explanation of why interventions to raise transfer often have limited effects [38].

There is empirical evidence that indicates the existence of different valence subgroups. Firstly, the factor structure of personal and nonpersonal cognitive valences in previous evaluations of the UMTM differed by study. For example, participants in the study of De Brabander and Martens [45] and De Jong et al. [48] did not seem, on average, to distinguish between personal and nonpersonal positive cognitive valence, whereas participants in other studies did [36,37,47,49]. This indicates that particular valences are more salient in predicting transfer intention in some samples than in others and suggests the possibility of deriving valence profiles in which groups of individuals differ in their manifestation of each valence type.

Secondly, previous research provided more specific evidence for the existence of (transfer) motivation profiles in the context of transfer of training. Chung and Chapman [50] showed that theoretically relevant profiles could be derived for motivation to learn within employee trainings. Moreover, Quesada-Pallarès et al. [27] provided evidence for transfer motivation profiles. In their study, they conceptualized transfer motivation as intentions that are formed by different components, such as perceived transfer control, subjective norms toward transfer and attitudes toward transfer (e.g., positive and negative feelings). The latter can be translated to the affective valences of the UMTM. In line with the study by Chung and Chapman [50], Quesada-Pallarès et al. [27], through cluster analysis, distinguished three subgroups that scored differently on transfer intention and transfer of training. In these subgroups, high positive feelings in relation to transferring training content coexisted with low negative feelings and vice versa [27]. This provides evidence against the independence of positive and negative affective transfer motivation as outlined by De Brabander and Martens [15]. However, Quesada-Pallarès and colleagues [27] were the first to examine transfer motivation profiles and did not include cognitive motivational types that are comparable to the cognitive valences of the UMTM. As such, more research is warranted.

The aforementioned two studies [27,50] also showed that clusters differ in transfer intention and transfer of training. That is, profiles that scored higher on high-quality motivation (i.e., intrinsic motivation and mastery orientation) also scored higher on transfer motivation and transfer intention than profiles that scored lower on these types of motivation. On the other hand, trainees who scored higher on low-quality motivation (i.e., performance avoidance orientation and extrinsic motivation) did not necessarily score lower on transfer motivation and transfer intention [50]. Moreover, subgroups scoring higher on positive affective types and lower on negative affective types of transfer motivation also scored higher on transfer intention and transfer of training [27]. However, as empirical evidence into these mechanisms is still scarce, more research is required. This could aid our understanding of which combinations of transfer motivation manifestations are more desirable for stimulating transfer intention and transfer of training.

More research is also required into whether members of transfer motivation profiles vary in perceived personal and contextual antecedents that influence different types of transfer motivation. Previous research in the field of organizational psychology showed that individuals scoring higher on antecedents of motivation (e.g., organizational support) were more likely to belong to profiles scoring higher on higher-quality forms of motivation (i.e., autonomous motivation) and lower on lower-quality forms of motivation (e.g., controlled motivation) [51,52]. As such, trainees who score higher on the personal and contextual UMTM antecedents might also score higher on positive valences and lower on negative valences. However, this has yet to be empirically tested. Studying this in the context of transfer of training could provide insight into which antecedents should be paid (more) attention to for specific groups of individuals.

1.4. This Study

To sum up, this study employs a person-centered approach to investigate individual differences in combinations of valence types (i.e., transfer motivation profiles). It also examines how these profiles differ on personal and contextual antecedents and how these profiles differ on transfer intention and transfer of training. This study achieves this by employing latent profile analysis (LPA). Investigating individual differences in combinations of predictors of transfer can be valuable for the transfer of training literature. It can provide recommendations to scholars examining predictors of transfer about whether such individual differences should be considered to predict the extent to which transfer of training occurs or not. This leads to the following research questions:

1. What profiles with different configurations of affective and cognitive valences for transfer of training can be distinguished among trainees?
2. To what extent do members of valence profiles differ in their perception of task-specific antecedents of the UMTM?
3. To what extent do valence profiles differ in transfer intention and transfer of training?

Based on previous studies and the UMTM literature [27,36,37,44–52], we formulated the following hypotheses. We expect the following:

1. Multiple affective and cognitive valence profiles can be distinguished.
2. Within profiles, relatively high positive affective valences co-occur with relatively low negative affective valences.
3. Within profiles, manifestations of specific cognitive valence types do not depend on manifestations of other cognitive valence types.
4. manifestations of positive and negative personal and nonpersonal cognitive valences co-occur independently of each other.
5. Individuals who score higher on the UMTM antecedents belong to profiles scoring higher on positive valences and lower on negative valences.
6. Profiles that score higher on positive valences also score higher on transfer intention and transfer of training.

2. Materials and Methods

2.1. Sample and Procedure

To test these hypotheses, we employed a longitudinal survey design. Our study was conducted at the Dutch judicial training institute and the Dutch police academy, which provide trainings to judicial employees and employees working for the police. Data were collected among trainees who participated in one of 264 included trainings. Of the included trainings, 129 (48.9%) were provided by the judicial training institute and 135 (51.1%) by the police academy. Trainings were selected if they (1) covered a specific skill or content (e.g., acquiring skills in working with a new type of software), since the UMTM focuses on task-specific behavior, and (2) using its content in practice was not mandatory. The application would otherwise not be the result of motivation but due to the obligation of applying the training content.

Collecting data within the judiciary and police contexts provided us with the possibility of including a range of different types of employees. Within the judiciary context, employees are more likely to be women, older and more experienced [53], whereas employees of the police are more often men, younger and less experienced [54]. Moreover, judicial employees perform relatively more cognitive-oriented work, whereas police officers have a relatively more executive-oriented profession. Including a wider range of employees and types of work increased the generalizability of this study to other contexts. The characteristics of the sample can be found in Table 1.

Table 1. Characteristics of the sample.

Demographic Characteristic	Judicial Training Institute	Police Academy	Total Sample
Number of participants T1 (response rate)	595 (45.5%)	527 (55.1%)	1122 (49.5%)
Indicated transfer at T2 (response rate)	458 (35.0%)	270 (28.2%)	728 (32.1%)
Filled in questionnaire at T1 and indicated transfer at T2 (response rate)	345 (26.4%)	188 (19.6%)	533 (23.5%)
Total number of unique participants (response rate)	706 (54.0%)	611 (63.8%)	1317 (58.1%)
Number of trainings	129	121	250
Range in number of participants per training	1–12	1–18	1–18
Mean age in years (SD)	40.71 (11.50)	38.75 (10.36)	39.89 (11.03)
Percentage women	81.4%	30.4%	57.5%
Mean experience in years (SD)	7.00 (8.41)	5.05 (5.49)	6.12 (7.29)
Type of work (percentage of the whole sample)	Executing (59.5%)	Executing (88.5%)	Executing (73.8%)
	Supporting (37.0%)	Supporting (9.2%)	Supporting (23.3%)
	Governing (3.5%)	Governing (2.3%)	Governing (2.9%)
Profession	Legal assistant (42.3%)	Police officer (32.8%)	Legal assistant (22.4%
(percentage of the whole sample)	Administrative assistant 28.8%)	Investigator (26.1%)	Police officer (15.4%)
	Judge (6.2%) Administrative judicial assistant (5.2%) Manager (3.0%)	Manager (11.2%) Apprentice (9.5%) Security (2.1%) Intelligence (1.3%)	Administrative assistant (15.2%) Investigator (12.3%) Manager (7.3%) Apprentice (4.5%) Judge (3.3%)
	Other (14.5%)	Other (17%)	Other (22.9%)

To compare the sample characteristics with the representativeness of the whole population, we compared the average age and proportion of women of all employees working within the judiciary or the police context [53,54] with a one-sample *t*-test. The average age of the sample within both the judiciary ($t(594) = -9.86$, $p < 0.01$) and police contexts ($t(526) = -14.29$, $p < 0.001$) was significantly lower than that of the population. Moreover, our sample contained significantly more women ($t(590) = 14.16$, $p < 0.01$) than the number of women working in the judiciary context, whereas our sample contained significantly fewer women than the number of women working for the police ($t(518) = -2.11$, $p = 0.04$).

All trainings focused on providing skills rather than knowledge. Both soft and hard skill trainings were represented in the selected trainings. A hard skill training is more focused on teaching specific technical skills such as computer programming or how to fill in a judicial report, whereas a soft skill training is more focused on inter- and intrapersonal skills such as teamwork and communication [55]. A total of 104 (39.4%) trainings were categorized as hard skill trainings, whereas 160 (60.6%) trainings were categorized as soft skill trainings. The amount of training days ranged between 36 full days and half a day. Moreover, 128 (48.5%) trainings were provided in-person, whereas the other 136 (51.5%) were provided online.

Participants filled in a questionnaire directly after the training. Transfer of training was measured after six weeks. In the transfer of training literature, the time period between training and transfer of training measurement varies, ranging between three weeks and one year [4,46,56–59]. In this study, it was co-decided by a selection of teachers from the trainings that six weeks would be sufficient for participants to have opportunities to use training content in practice.

All participants of the included trainings were asked to participate in the study at the end of the training. Partaking was voluntary and without incentives, and we collected data between December 2019 and June 2021.

2.2. Measures

An adapted version of the UMTM questionnaire was used to measure the UMTM components (see Table 2) [36], which consists of self-report items for the UMTM components and transfer of training. Except for positive and negative cognitive valence, all components were measured by one item that could be answered on a bipolar seven-point Likert answering scale.

Table 2. Items and answering scales for the questionnaire ([45], adapted by [48]).

Construct	Item	Answering Scale
1. Sense of personal autonomy	When applying this course's content in my job, I would feel I did so [. . .]	Completely out of my own volition–Completely out of experienced pressure
2. Perceived freedom of choice	When putting the things that were offered in this course into practice, I will have [. . .] opportunities for free choice	Very much–Very little
3. Sense of personal competence	I personally feel [. . .] to successfully apply the knowledge, skills, and insights that I acquired in this course	Very able–Not able at all
4. Perceived external support	I find the facilities in our court to apply what I have learned successfully [. . .]	Very obstructive–Very conducive
5. Subjective norm	I think that colleagues who are important to me would assess me applying what I have learned during the course as [. . .]	Not positive at all–Very positive
6. Sense of personal relatedness	I feel [. . .] with colleagues that are involved when I apply the learned content in practice	Closely connected–Barely connected
7. Positive affective valence	When applying the knowledge, skills, and insights that I acquired in this course, I would [. . .] have a positive feeling	Very often–Rarely or never
8. Negative affective valence	When applying the knowledge, skills, and insights that I acquired in this course, I would [. . .] have a negative feeling	Rarely or never–Very often
9. Positive cognitive valence personal	Considering the positive consequences, applying the course content in my job would be [. . .]	Not or hardly rewarding–Very rewarding
10. Positive cognitive valence nonpersonal	Considering the positive consequences, applying the course content in my job would be [. . .] for my team	Not or hardly rewarding–Very rewarding
11. Negative cognitive valence personal	The costs and unwanted consequences of applying the course content in my job would be [. . .]	Very heavy–Negligible
12. Negative cognitive valence nonpersonal	The costs and unwanted consequences of applying the course content in my job would be [. . .] for my team	Very heavy–Negligible
13. Transfer intention	I am going to apply the things that I have learned during the course in my job.	Completely disagree–Completely agree
14. Transfer of training	To what extent did you put the learned content into practice?	Not at all–Very much

Note. Items 1, 2, 3, 6, 7, 11 and 12 were recoded so that a high value would indicate more of the measured construct.

Using one item per construct can be beneficial as it substantially shortens a questionnaire in comparison to multiple-item questionnaires. This increases the likelihood that participants are willing to fill in a questionnaire [60]. Previous psychological research has provided evidence that one-item-per-construct questionnaires are able to reproduce the nomological network as good as multi-item-per-construct questionnaires and that they yield content validity [60–63]. Moreover, studies also found support for the reliability of one-item-per-construct questionnaires [60,62].

Previous research has also provided evidence for the convergent validity of the one-item-per-construct questionnaire of the UMTM, as constructs were related to each other in accordance with the dynamics of the UMTM in the transfer of training context [47–49]. However, the reliability of this questionnaire cannot be inspected through conventional statistics (e.g., Cronbach's α or McDonald's ω) when one item per construct is used. A method to indirectly assess reliability is assessing SEM model fit coefficients. These coefficients were originally introduced as coefficients to evaluate the reliability of latent structural equated scores [64]. Moreover, they are used "to avoid models with superfluous parameters that assume meaningless values" [65] (p. 136). As unreliable item response patterns are not able to predict or correlate with responses on other items, model fit coefficients inform about the unreliability in item responses. Thereby, we argue that by examining the concurrent validity of the latent structural equated scores, we indirectly assess the reliability of those scores. Herein, reliability is understood as an indicator of score quality and not as an indicator of score precision. Estimates of score precision are provided by the standard errors of the model parameters [66].

We employed this method to test for reliability on the one-item-per-construct questionnaire used in this study. We constructed a path model in which the components of the UMTM were related to each other in accordance with the dynamics of the UMTM. In this model, we constrained the relationships between the components in the direction that was hypothesized in the study by De Brabander and Martens in which the UMTM was introduced [28]. That is, when a positive relationship was expected between specific UMTM components, we constrained the relationship between these constructs to be positive. Such constraints were employed throughout the whole model. If items consistently did not predict or correlate with responses on other items in line with the expectations of the UMTM, this would provide an indication of unreliability. Eventually, this would also lead to a poorer model fit as indicated by SEM coefficients.

To test the model fit of this model, we assessed multiple goodness-of-fit indices. For RMSEA and SRMR, a value below 0.08 indicated a sufficient fit, and a value below 0.05 was classified as good. For TLI and CFI, a value above 0.90 indicated a sufficient fit and above 0.95 was interpreted as good [67]. The path model showed a good fit to the data ($\chi^2(100) = 407.04$, $p < 0.01$; RMSEA = 0.05 (0.05; 0.06); CFI = 0.95, TLI = 0.92, SRMR = 0.05) and that the relationships between the items were consistently in line with the expectations of the dynamics of the UMTM as outlined by De Brabander and Martens [28]. Thus, these outcomes provide evidence for the concurrent validity of the one-item-per-construct measure and therefore also provide indirect support for its reliability.

Moreover, we also measured some components with multiple items. For nonpersonal cognitive valence, participants indicated for different stakeholders whether applying training content would be valuable (or not). These stakeholders differed by work context. For the judiciary context, these were the team, court, judiciary and litigant. For the police context, these were the team, sector, police task and civilian. Stakeholders were matched on their level of generality, leading to the following matches: court/sector, judiciary/police task and litigant/civilian. In addition, feasibility appraisal was measured based on sense of personal competence and perceived external support.

For these components, we performed a confirmatory factor analysis (CFA). The items that refer to different stakeholders to measure nonpersonal cognitive valence loaded on two factors, one for positive and one for negative nonpersonal cognitive valence. Sense of personal competence and perceived external support loaded on the feasibility appraisal factor. Multicollinearity, linearity and univariate and multivariate normality of the scores were checked [68]. All assumptions were met. Model fit was sufficient when a correlation was added between the error terms of the items regarding the judiciary/police task and the litigants/civilian of the field for both positive and negative cognitive valence ($\chi^2(30) = 53.15$, $p = 0.01$; RMSEA = 0.03 [.01; 0.04]; CFI = 0.99, TLI = 0.99, SRMR = 0.02). We also estimated Omega (ω), which can be used to investigate the reliability of latent variables [69]. These were $\omega = 0.66$ for feasibility appraisal and $\omega = 0.80$ for both positive and negative nonpersonal cognitive valence. The final CFA model was used as a reference for making sum scores of nonpersonal positive and negative cognitive valence and feasibility appraisal, which were used in further analyses.

2.3. Data Analysis

To analyze the data, Mplus 8.0 was used [70], and LPA was performed. We chose to employ LPA over other clustering techniques as its model-based approach does not require measurement scaling [71]. It also allows for the use of formal tests to make decisions regarding the number of clusters included in the analysis. As such, performing LPA has several advantages over more traditional clustering methods [71]. Prior to employing LPA, multivariate outliers were checked (see Pastor et al. [25]). Analyses showed two outliers, leading to the exclusion of two participants.

LPA classifies individuals from a heterogeneous group into homogeneous subgroups (i.e., profiles). Individuals within these subgroups show comparable patterns in their responses to indicators [25]. Indicators in this case were two items measuring personal positive and negative cognitive valences, two scale variables of items measuring positive and negative nonpersonal cognitive valences, and two items measuring positive and negative affective valences [25].

For these indicators, LPA can freely estimate means, variances and covariances within profiles. (Co)variances can also be constrained to be equal across profiles to reduce model complexity (see Pastor et al. [25] for a discussion on LPA parameterizations). In this study, means were freely estimated across profiles, and (co)variances were constrained to be equal across profiles because convergence issues emerged when more parameters were freely estimated for three or more profiles.

To analyze the data, we followed the procedure for performing LPA as outlined by Pastor et al. [25]. Firstly, we estimated a number of different profiles to explore the number of profiles that could best and most informatively represent the data. These models concerned profile solutions with varying numbers of profiles, which were compared in terms of profile uniqueness, model fit, classification accuracy and profile sizes [25].

In line with [25,72], model fit was investigated with the Akaike information criterion (AIC), Bayesian information criterion (BIC), the sample-size-adjusted BIC (SSA-BIC), the Lo–Mendell–Rubin log-likelihood test (LMRT) and the bootstrapped likelihood ratio test (BLRT). For the AIC, BIC and SSA-BIC, smaller values indicate better model fit. The LMRT and the BLRT are significance tests of the null hypothesis that there is no increase in model fit between a model with K-1 and K profiles. A significant LMRT or BLRT therefore indicates that adding a profile improves model fit [25,71]. The classification accuracy of the different models was evaluated through the entropy statistic. A high entropy indicates that participants are more accurately classified into the correct profile [25]. Finally, solutions with profiles smaller than 5% of the sample were not considered as they may be spurious and not contain substantive insights that are relevant for practice [73]. The final model was used to investigate different profiles that were prevalent within the sample (RQ1).

To answer RQ2 and RQ3, the antecedents and outcome variables were added to the final LPA model as auxiliary variables [74]. We considered these variables to be auxiliary as there is limited empirical evidence for the direction of effects between the UMTM antecedents, different valences and outcome variables. In such a case, it is recommended to add variables to LPA models as auxiliary [74]. We also added demographic characteristics to investigate potential differences between the profiles on the demographic variables, as previous research has indicated that some of these characteristics can predict transfer motivation and/or transfer of training [9,15,75,76] and might explain why specific individuals belong to specific profiles. The effects of all demographic variables, except for work domain, gender and training institute, were analyzed using the BCH method, which is considered to be a valid method for analyzing mean differences between profiles on continuous variables [77]. Work domain, gender and training institute are categorical auxiliary variables and are therefore recommended to be analyzed using the DCAT method [77].

To answer RQ2, the means of the UMTM antecedents were compared across profiles from the final LPA model. To answer RQ3, profile mean differences in transfer intention and transfer of training were investigated.

3. Results

3.1. Descriptive Statistics

Table 3 provides an overview of the correlations, means and standard deviations of the different UMTM components and demographic characteristics. The correlations between the components are in line with the proposed dynamics of the UMTM. Exceptions are the correlations of personal and nonpersonal negative cognitive valences with sense of personal relatedness, which are not significant. In addition, both personal and nonpersonal negative cognitive valences do not correlate with transfer of training.

Table 3. Correlation matrix, means and standard deviations of the UMTM components and demographic characteristics.

	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.	14.	15.
1. Perceived freedom of action															
2. Sense of personal autonomy	0.35 ***														
3. Feasibility appraisal	0.30 ***	0.32 ***													
4. Sense of personal relatedness	0.16 ***	0.19 ***	0.29 ***												
5. Subjective norm	0.22 ***	0.30 ***	0.43 ***	0.26 ***											
6. Positive affective valence	0.33 ***	0.39 ***	0.39 ***	0.29 ***	0.37 ***										
7. Negative affective valence	−0.23 ***	−0.26 ***	−0.30 ***	−0.15 ***	−0.21 ***	−0.34 ***									
8. Positive cognitive valence (p)	0.17 ***	0.24 ***	0.38 ***	0.17 ***	0.33 ***	0.43 ***	−0.19 ***								
9. Positive cognitive valence (np)	0.08 **	0.10 **	0.40 ***	0.25 ***	0.30 ***	0.37 ***	−0.20 ***	0.63 ***							
10. Negative cognitive valence (p)	−0.20 ***	−0.20 ***	−0.20 ***	−0.01	−0.17 ***	−0.15 ***	0.20 ***	−0.10 ***	−0.04						
11. Negative cognitive valence (np)	−0.15 ***	−0.18 ***	−0.19 ***	−0.001	−0.14 ***	−0.16 ***	0.19 ***	−0.13 ***	−0.08 *	0.86 ***					
12. Transfer intention	0.10 ***	0.14 ***	0.33 ***	0.14 ***	0.28 ***	0.30 ***	−0.17 ***	0.35 ***	0.35 ***	−0.08 *	−0.08 *				
13. Transfer of training †	0.12 **	0.19 ***	0.25 ***	0.15 ***	0.25 ***	0.26 ***	−0.19 ***	0.31 ***	0.23 ***	−0.07	−0.002	0.15 ***			
14. Experience	0.04	0.04	−0.01	0.02	−0.04	0.02	0.02	−0.12 ***	−0.13 ***	−0.08 *	−0.07	−0.02	−0.06		
15. Age	0.11	−0.07 *	−0.07 *	0.01	−0.07 *	0.03	0.06	−0.12 ***	−0.21 ***	−0.14 ***	−0.14 ***	−0.10 ***	−0.11 *	0.54 ***	
Mean	5.41	5.86	5.27	5.23	5.45	5.59	2.44	5.84	5.50	2.50	2.59	5.61	4.55	6.12	39.89
Standard deviation	1.20	1.21	0.90	1.24	1.16	0.96	1.25	1.14	1.24	1.58	1.50	1.65	1.48	7.29	11.03

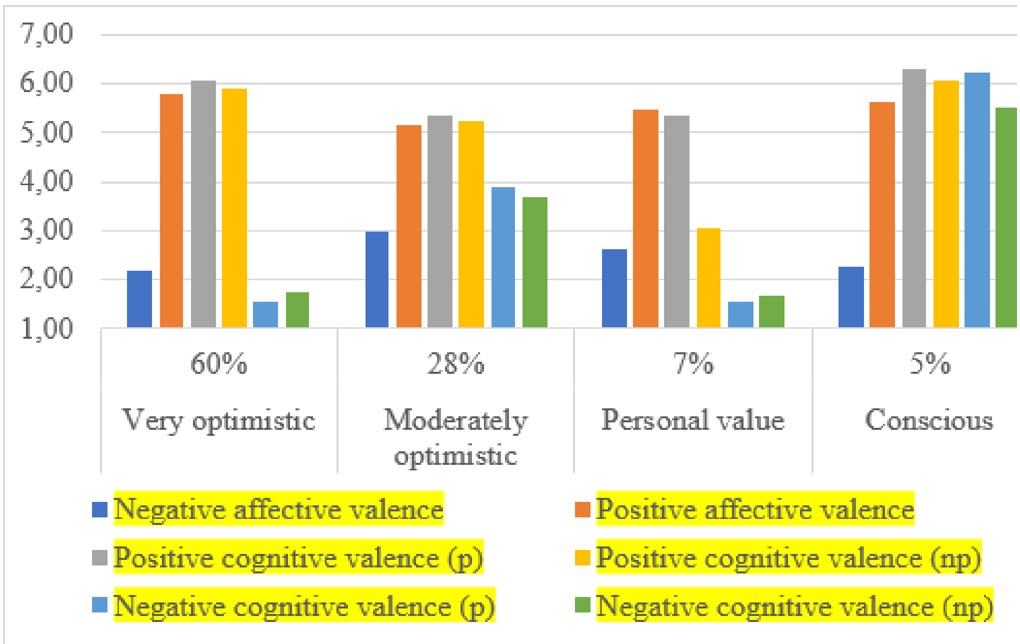
Note: p = personal, np = nonpersonal. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. † measured after six weeks.

3.2. Valence Profiles

Table 4 displays model fit statistics of the different LPAs. The LMRT was consistently significant when profiles were added. Moreover, the AIC, BIC and SSA-BIC improved when more profiles were added, whereas the entropy value only decreased slightly with a four-profile solution. On the other hand, the BLRT did not improve significantly with a four-profile solution or beyond. Moreover, a five-profile solution or more contained profiles with less than 5% of the sample, which increased the chance of getting spurious outcomes within these small profiles [73]. A five-profile solution or beyond was therefore excluded. Based on the BLRT, choosing a three-profile solution would make the most sense. However, the AIC, BIC, SSA-BIC and LMRT favored a four-profile solution. Also, the four-profile solution proved theoretically more interesting than the three-profile solution, as the fourth profile is distinctive from the other three profiles. That is, a four-profile solution included a profile that reported a discrepancy in experiences of personal and nonpersonal cognitive valences, which was not apparent in the three-profile solution. Therefore, the four-profile solution was chosen for further analysis (see Figure 2). Table 5 provides an overview of the (co)variances between the valences of the profiles.

Table 4. Model fit of the different profile solutions.

K	AIC	BIC	SSA-BIC	Entropy	LMRT	BLRT	% Smallest Cluster
1	17.585.754	17.721.324	17.635.564	n/a	n/a	n/a	n/a
2	17.367.318	17.538.035	17.430.042	0.74	<0.001	<0.001	25%
3	17.179.658	17.385.522	17.255.295	0.79	<0.001	0.01	7%
4	17.047.918	17.288.930	17.136.469	0.78	<0.001	0.07	5%
5	16.901.169	17.177.328	17.002.634	0.80	<0.001	0.06	3%



Note. p = personal, np = nonpersonal

Figure 2. The indicator means of the four-profile solution.

Table 5. Covariances and variances of the valences in the different profiles.

Covariances	NAVAL	PAVAL	PCVpers	PCVnp	NCVpers	Variance
NAVAL						1.43
PAVAL	−0.32					0.86
PCVpers	−0.15	0.39				1.18
PCVnp	−0.14	0.32	0.69			0.92
NCVpers	0.11	0.02	−0.01	−0.06		0.48
NCVnp	0.14	−0.02	−0.04	−0.08	0.37	0.87

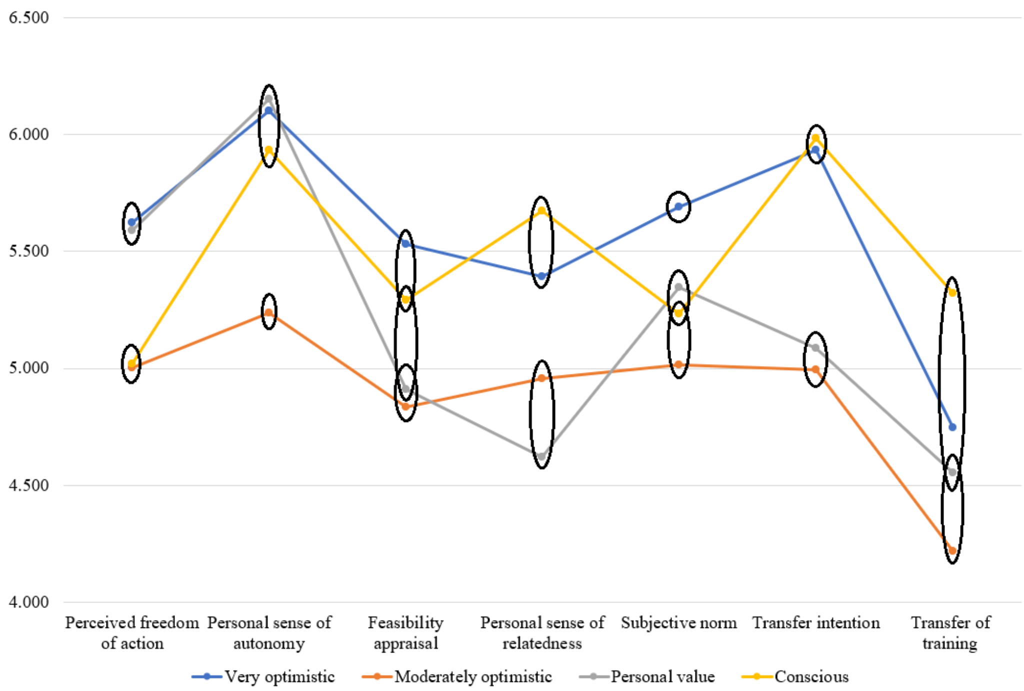
Note. NAVAL = negative affective valence, PAVAL = positive affective valence, PCVpers = positive cognitive valence personal, PCVnp = positive cognitive valence nonpersonal, NCVpers = negative cognitive valence personal, NCVnp = negative cognitive valence nonpersonal.

The first and second profiles are the biggest profiles with, respectively, 60% and 28% of the participants. The first profile contains the very optimistic trainees. Members of this profile scored high on positive valences and low on negative valences. Thus, they foresee strong positive and weak negative feelings and many positive and few negative consequences when they would apply training content in practice. The second profile is described as the moderately optimistic trainees. Members of this profile scored high on positive valence and average on negative valence. They seem to experience an average amount of negative feelings and negative consequences, strong positive feelings and many positive consequences when they consider transferring the training content. Differences between positive and negative valences are smaller in this profile than among the very optimistic trainees.

The third and fourth profiles occurred less frequently among participants (respectively, 7% and 5% of the participants). The third profile contains the personal value trainees. Members of this profile scored high on positive affective valence and personal positive cognitive valence. Moreover, they scored low on nonpersonal positive cognitive valence and the negative valences. This profile shows a clear distinction between personal and nonpersonal positive cognitive valence. Members of this profile seem to be mostly motivated by positive feelings and seeing profits for themselves when they consider using the training content in practice. The fourth profile consists of the conscious trainees. Members of this profile scored the highest on both positive and negative cognitive valence and on positive affective valence. Moreover, members of this profile scored low on negative affective valence. Thus, they strongly foresee positive and negative consequences for themselves and others and anticipate strong positive and weak negative feelings when they would apply the training content in practice.

3.3. Mean Differences in the Antecedents, Outcome Variables and Demographic Characteristics

As a next step, we added the UMTM antecedents, outcome variables and demographic characteristics to the model. Figure 3 depicts mean differences between the profiles in the antecedents and outcome variables. In terms of mean patterns, it can be found that the moderately optimistic trainees are a parallel of the mean pattern of the very optimistic trainees. The mean pattern of the personal value and conscious trainees is also largely in line with the mean patterns of the moderately and very optimistic trainees. However, the personal value and conscious profiles mirror each other in relatedness and subjective norm. That is, the personal value trainees score relatively low on sense of personal relatedness and relatively high on subjective norm in comparison to the other components for this profile, whereas the opposite is the case for the conscious trainees.



Note. Means in the ellipses that do not overlap are significantly different from each other.

Figure 3. Mean scores between the clusters of the UMTM antecedents and outcome variables.

In terms of mean differences between the profiles, the very optimistic trainees scored the highest or otherwise belonged to the highest-scoring trainees on all antecedents and outcome variables, whereas the moderately optimistic scored the lowest or belonged to the lowest-scoring profiles. The personal value trainees scored in between the very and moderately optimistic trainees on most antecedents and the outcome variables. Moreover, the conscious trainees scored the highest on transfer intention and transfer of training despite the high scores on negative cognitive valence.

We also found mean differences between the profiles in the demographic characteristics (see Table 6). Trainees belonging to the personal value profile had significantly more job experience than members of the other profiles. Moreover, they were also significantly older and were more likely to be women than members of the other profiles. In addition, trainees belonging to the conscious profile were significantly younger than trainees in the other profiles. Furthermore, trainees belonging to the very optimistic and conscious profiles were significantly more likely to be working for the police, whereas members of the moderately optimistic and personal value profiles were more likely to work within the judiciary context and to be a woman. Finally, we also found differences between the profiles in terms of job type. Members of the personal value profile were more likely to have a supportive job and less likely to have executive and governing jobs in comparison to members of the other profiles.

Table 6. Differences between profiles in the demographic characteristics.

Variable	Very Optimistic Trainees (60%)	Moderately Optimistic Trainees (28%)	Personal Value Trainees (7%)	Conscious Trainees (5%)	Chi-Square
Experience (mean)	6.14 $_b$	5.59 $_b$	8.64 $_a$	4.97 $_b$	8.92 *
Age (mean)	40.13 $_b$	39.24 $_b$	44.98 $_a$	34.04 $_c$	25.6 ***
Gender (odds of identifying as a female)	1.00 $_b$	1.45 $_a$	2.27 $_a$	0.94 $_b$	11.47 **
Work field (odds of working for the police)	1.00 $_a$	0.57 $_b$	0.18 $_c$	1.20 $_a$	48.79 ***
Executive vs. supportive (odds of having a supportive job)	1.00 $_b$	1.23 $_b$	3.43 $_a$	0.95 $_b$	11.51 **
Governing vs. executive (odds of having an executive job)	1.00 $_a$	1.81 $_a$	0.20 $_b$	1.06 $_a$	5.64
Governing vs. supportive (odds of having a supportive job)	1.00 $_a$	2.23 $_a$	0.36 $_b$	1.10 $_a$	6.15

Note. Mean scores are significantly different if they have different subscripts. Chi-square indicates the effect size of the mean differences between the profiles. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. In addition, the very optimistic profile was used as reference profile for the odds ratios.

4. Discussion

Previous transfer of training research investigating the association between transfer motivation and transfer of training often found mixed effects for the magnitude of the correlation between both components [6,8,9]. One explanation for this is that previous research often approached transfer motivation one-dimensionally [15]. Moreover, previous transfer of training research often did not take into account that individual trainees can differ in terms of combinations of different antecedents, such as transfer motivation, that predict the extent to which transfer occurs or not [18]. As such, there is a call for more person-centered transfer of training research [18].

The aim of this study was to investigate whether transfer motivation profiles exist and how these profiles differ in transfer intention and transfer of training. Moreover, we investigated whether profile membership could be explained by the antecedents of the UMTM. Based on previous research [27,36,37,44–52], we hypothesized that multiple groups of individuals exist that differ in the configuration of affective and cognitive valences. Moreover, we expected that, within profiles, high manifestations of positive affective valences co-occur with low manifestations of negative affective valences and vice versa. For cognitive valences, on the other hand, we expected that manifestations of positive and negative personal and nonpersonal cognitive valences co-occur independently from each other within profiles. Furthermore, profiles scoring higher on positive valence also contained trainees scoring higher on the antecedents. Finally, we hypothesized that profiles scoring higher on positive valence also scored higher on transfer intention and transfer of training.

4.1. *Distinguishing Motivational Valence Profiles for Transfer of Training*

Our first aim was to investigate whether transfer motivation profiles exist. We found support for our first hypothesis, as we found that multiple groups of individuals exist that differ in their manifestation of valences for transfer (i.e., transfer motivation). Four valence profiles with a distinct, theoretically relevant configuration of valences for transfer could be distinguished. These were the 'very optimistic', 'moderately optimistic', 'personal value' and 'conscious' profiles. Finding different profiles for transfer motivation is in line with studies that employed different motivation theories and found motivation profiles for other activities than transferring training content to work practice [19,20,22–26,78]. Moreover, it is also in line with the study by Quesada-Pallarès et al. [27], who also found distinctive transfer motivation profiles. Most trainees (88%) differed in mean scores on the valences (i.e., belonging to the very and moderately optimistic profiles), whereas the remaining 12% of trainees deviate from the aforementioned two profiles with a different valence configuration (i.e., members of the personal value and conscious profiles).

Structures of the latter two profiles also provide evidence for the possibility of independence between cognitive valences, in line with our third hypothesis. Some individuals distinguished between positive consequences for themselves and others (i.e., personal value profile), and some individuals strongly foresaw both positive and negative consequences for themselves and others (i.e., conscious profile) when they considered applying the training content. This independence was not found for affective valences. Consistently across profiles, negative affective valence was lower when positive affective valence was higher. This is in line with our second hypothesis and aligns with the study by Quesada-Pallarès et al. [27], who found that a low intention to transfer cluster scored lower on positive feelings and higher on negative feelings to transfer in comparison to clusters with a higher intention to transfer. As such, our outcomes underline a lack of affective ambivalence towards applying training content in which positive and negative feelings exist concurrently among trainees [79]. On the other hand, this might also be the result of the measure used in our study. We asked participants to rate their positive and negative feelings about applying the training content separately. Yet, participants are not always able to suppress positive feelings when they answer a question about their negative feelings and the other way around [80]. Moreover, previous research has indicated that ambivalence for exhibiting specific work behavior does exist [81,82].

4.2. Profiles and the UMTM Antecedents

Our second aim was to investigate whether profiles differed in the UMTM antecedents. Our outcomes indicated that members of the profiles differed mostly in the level of the antecedents, whereas score patterns were relatively comparable across profiles. Furthermore, trainees with higher scores on the antecedents belonged to profiles scoring lower on negative affective valence and higher on positive valences. This is in line with previous research, which also showed that profiles with bigger differences between high- and low-quality work motivation scored higher on antecedents of motivation [51,52]. This was also found for transfer motivation [27]. Nevertheless, profiles scoring higher on the antecedents did not necessarily score higher on positive cognitive valence, which is not in line with Graves et al. [51] and Gillet et al. [52]. As such, we found partial support for our fourth hypothesis.

Instead, it seems that profiles with specific deviations in score patterns of the antecedents also have specific differences in positive and negative cognitive valence. For example, members of the personal value profile scored relatively low on sense of personal relatedness and high on subjective norm in comparison to patterns of antecedents in the other profiles. They also scored low on nonpersonal and high on personal positive cognitive valence. Furthermore, members of the conscious profile scored the opposite on the sense of personal relatedness and subjective norm and scored high on both positive and negative cognitive valence. It seems that if trainees feel less connection with colleagues, they also see less meaning for others to apply training content. This is in line with previous research in which a lower sense of relatedness was negatively associated with the perceived meaningfulness of work [83]. On the other hand, feeling more of a connection with colleagues and expecting that colleagues would disapprove of the application of training content might implicate that trainees foresee more negative consequences, for example, as to what extent applying the training content matches with organizational norms [84].

4.3. Profiles and the Outcome Variables

Our third aim was to investigate whether motivational profiles differed in transfer intention and transfer of training. Our results suggest that multiple types of transfer motivation play a role in transfer intention and transfer of training. More specifically, our outcomes showed that trainees belonging to profiles that scored higher on positive affective valence and lower on negative affective valence scored higher on transfer intention and transfer of training. The role of affective valence is in line with previous UMTM research. These studies showed that negative affective valence is a negative predictor and positive affective valence is a positive predictor of readiness for action (of which transfer intention is an example) [36,37,45,47]. Moreover, our outcomes showed that it also matters whether both personal and nonpersonal positive cognitive valences are high in co-occurrence with high positive and low negative affective valence. Profiles scoring lower on nonpersonal positive cognitive valence also scored lower on transfer intention and transfer of training. As such, our outcomes provide support for our fifth hypothesis and are in line with previous research that indicates that profiles with bigger differences between high- and low-quality motivation scored higher on outcome variables [19,51].

However, our results also indicate that high negative cognitive valences in co-occurrence with high positive valences and low negative affective valence (i.e., the conscious profile) seems to be at least as beneficial for transfer intention and transfer of training as high overall positive valences combined with low overall negative valences. Despite the prospect of potential negative consequences as a result of training application, it seems that members of the conscious profile still intended to apply training content and eventually also transferred training content. Interestingly, trainees in this group were younger than members of the other groups. The socioemotional selectivity theory of Carstensen [85] states that if individuals perceive themselves as having more time left to spend on their work career, they are more willing to pursue skill acquisition. They might therefore be more easily motivated to transfer and more easily transfer training content regardless of the negative consequences.

Finally, our results showed that differences between profiles were bigger for transfer intention than transfer of training. This could be due to changes in configurations of the valences over time. Trainees might become less motivated to use training content in practice, resulting in smaller differences between profiles in transfer of training.

4.4. Theoretical Implications, Limitations and Directions for Future Research

The findings of this study have important implications for the transfer of training literature. This study underlines the need for transfer of training research to consider individual differences in patterns of antecedents of transfer between trainees. Even though our results show that most trainees have a relatively comparable pattern in transfer motivation types, they also unveil that trainees can have patterns in transfer motivation that clearly deviate from those of other trainees. Moreover, these trainees also have distinctive patterns in personal and contextual antecedents and score differently on transfer intention and transfer of training. As such, these results underline the necessity for transfer of training researchers to approach transfer motivation as a multidimensional construct, in line with previous transfer motivation research [10,13–16]. Moreover, this study corroborates the presumption of Baldwin et al. and Weiss and Rupp [17,18] that different patterns in antecedents of transfer of training between individuals exist that might explain differences in transfer of training. We, therefore, argue that more transfer of training research into the role of individual differences between trainees in patterns of antecedents of transfer of training is recommendable, as such differences might also be found for other components. Eventually, more person-centered research would provide further insight into the explanatory role of individual differences for the extent that transfer of training occurs.

Our results also provide further insight into the complex interplay of transfer motivation types. It seems that affective types of transfer motivation are co-dependent, whereas cognitive types can function independently from each other for a minor group of trainees. Additionally, cognitive types of transfer motivation seem to depend on the distribution of affective types of transfer motivation, perhaps because individuals tend to align their thoughts and feelings to avoid internal conflict. Yet, this also does not apply to all trainees. To further disentangle how trainees take feelings and possible consequences into consideration in their decision making to process applying training content, we recommend future transfer of training research to investigate this with a qualitative design [86]. This could give us more insight into the interplay between positive and negative cognitive types of transfer motivation, how this interplay can differ between trainees and how this eventually affects transfer intention and transfer of training.

We also have a number of recommendations for future research based on the limitations of this study. Firstly, due to limitations in sample size, we used a parameterization for the latent profile analysis in which the between-profile (co)variances were restricted to be equal. This can have implications for the profile solutions found in the LPA. For example, Vermunt and Magidson [87] demonstrated in their simulation study that unrestricted between-profile covariances can result in fewer profiles in comparison to when between-profile covariances are constrained to be equal. As such, differentiating variances and covariances between profiles may lead to a different number of profiles. However, the aim of this study was to examine if transfer motivation profiles exist and what effects these profiles have on relevant motivational variables. The aim was not to indicate which specific profiles exist within the population. To obtain more insights into the latter question, we recommend future research use bigger sample sizes to apply more complex parameterizations. Moreover, it could be interesting to conduct this research in different contexts, for example, in terms of work domain or type of profession. Even though the sample derived from the two contexts used in this study had considerable diversity in terms of age, gender, experience and type of work, it is unclear to what extent these findings translate to other contexts and/or countries.

Secondly, we used model fit coefficients to indirectly examine the reliability of the components of the UMTM. This strategy was employed because components were measured with one item. However, this strategy is imperfect and confounds the interpretation of reliability and predictive and/or concurrent validity. While, in our opinion, the estimates and outcomes of the analysis provide support that this measure is sufficiently valid and reliable for substantial interpretation and theoretical development, we advise future work to address this confound and more directly investigate reliability. This can be carried out by administering multiple items per construct and employing traditional reliability analyses (e.g., Cronbach's α). But we also advise researchers to explore other statistical models, for example, item response theory (IRT) [88] or unfolding models [89].

Thirdly, our study did not take other factors into account that could explain profile membership. For example, training quality can be predictive of transfer motivation [6] and transfer of training [4]. In addition, the extent to which a training is attended voluntarily or mandatorily might also have a predictive value for transfer motivation [14,90] and transfer of training [14]. We recommend future studies take these components into account to investigate the influence they have on profile membership.

Fourthly, due to a lack of empirical evidence regarding the causal relationships between the UMTM components, all variables but the valences were investigated as auxiliary variables in the latent profile analysis. As a result, it was not possible to investigate the predictive value of the antecedents for profile membership and whether the profiles predict the outcome variables. We recommend more research into the UMTM to further investigate the cause-and-effect relationship between its components. This can be achieved by conducting more longitudinal or experimental research.

4.5. Practical Implications

Our results provide multiple recommendations for trainers and policy makers. Firstly, it seems to be important for the majority of trainees to foster positive valences and diminish negative valences. This can be achieved by supporting the different antecedents among these trainees. However, our results also indicate that for a minor group of trainees, it is useful for trainers to put more emphasis on specific antecedents in comparison to other antecedents, for example, more emphasis on sense of personal autonomy in comparison to feasibility appraisal.

To tailor trainings more specifically to these groups of trainees, demographic characteristics such as age, gender, experience and type of work can be used as indicators of what specific needs specific trainees have. Based on these characteristics, trainers could form more homogeneous groups. This can make it more convenient for trainers to focus on enhancing specific antecedents for specific groups of trainees to enhance their transfer motivation and, eventually, transfer of training in comparison to groups that are demographically more mixed.

For example, trainees with a personal value profile tend to be older and more experienced trainees. They would require more support for raising perceived external support, sense of personal competence (i.e., feasibility appraisal) and sense of personal relatedness in comparison to members of other profiles. Perceived external support could be raised by ensuring that supervisors encourage trainees to use training content and sharing feedback with their employees about using training content [2]. Sense of personal competence could be raised by setting goals at the end of the training as to what trainees want to achieve by transferring training content [91]. Sense of personal relatedness could be supported by emphasizing that colleagues should take more time to listen to each other and that colleagues should signal more often that they are genuinely interested in each other. This can increase feelings of belonging toward other colleagues [92].

Trainers could also differentiate among trainees belonging to the conscious profile, who tend to be younger and less experienced. Among these trainees, more emphasis should be placed on supporting more freedom from the work environment and providing more support for subjective norm. Autonomy could be supported by ensuring that colleagues and managers use non-controlling language, provide meaningful rationales and provide more choices when employees aim to transfer training content [93]. Subjective norm could be supported by ensuring that multiple colleagues and supervisors of the same organization participate in the training. This can increase the chance that its content fits within the norms of the organization [83] and can raise positive attitudes among employees about applying the content [42].

5. Conclusions

To sum up, our study has provided valuable insights for transfer of training researchers and practitioners. This study has shown that examining differences in patterns of transfer motivation among individuals can provide insights into how these individual differences co-occur with differences in personal and contextual antecedents of transfer motivation, transfer intention and transfer of training. These insights underline the importance of transfer of training research employing a person-centered approach for explaining the extent to which transfer of training occurs and for understanding why the association between transfer motivation and transfer of training can differ considerably between trainees. Acquiring more insight into individual differences in patterns of transfer motivation and other predictors of transfer of training between individuals will enable us to develop finer-grained guidelines as to how transfer of training interventions could be tailored to specific groups of trainees to raise transfer motivation and, eventually, transfer of training. This can increase the likelihood that trainings have impact on organizations.

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Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The dataset analyzed during the current study is not publicly available due to the privacy regulations of both the police academy and judicial training institute. However, anonymous data are available from the corresponding author upon reasonable request.

Conflicts of Interest: The authors declare no conflict of interest.

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