ately interested in politics. Likewise, 48 percent say that they often participate in discussions about political issues with family and friends, and 44 percent say that this is the case occasionally. The variables political interest and frequency of political discussions are highly correlated ($r = .516$, $p < .05$). The respondents are also rather experienced with political day-to-day business. One out of five participants indicates that he or she frequently has direct experiences with politics, and 41 percent say that this is the case occasionally. 16 percent of the respondents frequently and 46 percent occasionally have indirect experiences with politics through relatives or friends. The subjects in general are not only interested in politics and experienced with the political day-to-day business; some of them also actively participate in politics. About one out of five participants is an active party member, 27 percent are engaged in an interest group and 10 percent even hold a political mandate.

Moreover, the sample in general shows a high level of use of the media for political information. More precisely, for at least 15 minutes on an average day, 85 percent of respondents use the radio, 69 percent read a local paper, 79 percent read a national paper, 81 percent watch political information on television, and 79 percent use the internet. The use of tabloids and free papers is less intensive among the participants. Only 15 percent of the respondents read a tabloid and 56 percent read a free paper for at least 15 minutes on an average day. All subjects use at least one of the different types of political media information for at least 15 minutes a day.

7.2.3. Data Analysis

In order to investigate the media's impact on political support, structural equation modeling (SEM) is used as it allows modeling the presumed relationship between the measured independent, dependent, and mediating variables. Generally, the literature mentions several advantages of SEM compared to regression models, for instance. First, SEM provides more accurate effect estimates. More precisely, if several measures of a construct are gathered and relationships among latent variables are analyzed, then SEM will control for measurement errors[91] and analyze unattenuated relationships. Latent variables are variables that are not directly observed but inferred from other variables that are observed and measured (so-called manifest variables). The relationship between latent variables and their indicators is described in measurement models. The measurement models of this study are presented in Appendix 10.3. Hence, structural equation models have two parts, i.e. measurement parts and structural parts. Structural parts estimate the structural coefficients between the latent and/or manifest variables. Using latent variables, SEM permits us to study the influence of one error-free construct on another, eliminating potential bias due to attenuation. The model controls for measurement error by estimating the

91 The term measurement error refers to "the extent to which random error affects the measurement of a given variable" (Bedeian, Day, & Kelloway, 1997, p. 786).

"true" correlation between variables. These adjustments for measurement error provide results based on hypothetical rather than obtained data (Bedeian, et al., 1997, p. 794f.). In general, measurement errors are considered a serious threat to causal analysis, because they affect the explained variance of an independent variable (Bedeian, Day, & Kelloway, 1997).

Second, SEM allows us to analyze precise processes which may explain changes in the outcome variables (Russell, Kahn, & Altmaier, 1998). The effect mechanisms are investigated by integrating mediating variables into the model. The importance of considering indirect effects in media effects, as well as the usefulness of SEM for investigations of mediation models, is emphasized by several authors (Brandl, 2004; Holbert & Stephenson, 2002, 2003; Matthes, 2007b). Another advantage of SEM compared to regression models is that more than one independent variable can be used and the independent variables can be highly correlated. In order to be able to investigate the data in this study based on SEM, the data collection took requirements of SEM into consideration, e.g. the use of several measures of a construct in order to be able to conceptualize latent variables and the recruitment of enough participants to ensure that the sample size is large enough.

The SEM analyses used EQS version 6.1 software (Bentler, 2006). The data were tested for univariate and multivariate normal distribution and strong outliers were excluded from data analysis. Extreme violations (moderate ones are given in parentheses) on the assumption of the univariate distribution are associated with skew values of at least 3 (2) and kurtosis of at least 20 (7) (West, et al., 1995). These values were not reached with the original variables. Mean-centered variables[92], however, showed some violations of univariate normality. Yuan, Lambert and Fouladi (2004) developed an extension of the Mardia test of multivariate kurtosis (1970, 1974) that can be applied to data with missing values. The normalized estimate is interpretable as a standard normal variate; the hypothesis of multivariate normality must be rejected if it is outside the range of -3 to +3 (Bentler, 2006, p. 282f.). For models with mean-centered variables the variate was outside this range.[93] Hence, the distribution-free Satorra-Bentler estimation as an alternative to Maximum-Likelihood estimation was applied (cf. Bentler, 2006, p. 137ff.). This method uses the Maximum-Likelihood estimation, but corrects test statistics and the standard errors (Benteler, 2006, p. 136ff., 289). In addition, robust methods might correct for deviations from the missing-at-random assumption.

Missing values were treated using the maximum likelihood-method (ML-imputation algorithm), also known as full information maximum likelihood (cf. Bentler, 2006, p. 285ff.; Wothke, 2000).[94] The appropriateness of imputing missing

92 Mean-centered variables were used for the computation of latent interaction variables.

93 Nonnormality problems in the context of estimating latent interaction effects might occur (Marsh, Hau, & Wen, 2004; Schermelleh-Engel, Klein, & Moosbrugger, 1998).

94 The values for those participants who dropped out of the study were not imputed. Subjects who did not participate in the final survey or did not complete any of the article surveys were excluded from the final data set that is the basis for the data analysis, because for them no

values depends on the characteristics of the missing data patterns. However, the ML-imputation algorithm does not necessitate that data are missing completely at random (MCAR: missingness depends on observed values in the data set); it can also be used with data missing at random, a weaker kind of mechanism (MAR: missingness depends on unobserved values) (Benteler, 2006, p. 276). As there is no statistical test whether this assumption holds for a given set of data, researchers are asked to carefully analyze the missing data patterns. In addition, using robust methods might correct for deviations from the MAR assumption. Because the analysis is based on imputed data, I generally applied the distribution-free Satorra-Bentler estimation as an alternative to Maximum-Likelihood estimation.

As regards the investigation of the assumed moderator effect, some studies use the arithmetic difference between preferences and perceptions (Kimball & Patterson, 1997), an approach that is consistent with the proximity model of candidate evaluation (Grynaviski & Corrigan, 2006). In proximity models of candidate evaluation, proximity scores indicate how close an individual's stand is to the stand of candidates, mostly with respect to policy issue positions. Other studies base their data analysis on comparisons between groups of people with congruent and incongruent preference-perception relationships (S. C. Patterson, et al., 1969). Another possibility would be to build the product of perceptions and preferences. Such an approach is suggested by the expectancy value model (Doll & Ajzen, 2008). To test whether process preferences would moderate the relationship between process perceptions and political support using SEM, I followed the latent interaction approach of an unconstrained model suggested by Marsh et al. (2004). Because process preferences were measured continuously, this approach appeared to be more applicable than a multigroup comparison based on arbitrary cut-off values. Marsh et al. (Marsh, et al., 2004) proposed testing for latent interactions by multiplying mean-centred indicators of predictor and moderator and specifying these products as indicators of the latent interaction factor. As suggested by Marsh et al. (2004), I estimated the latent interaction models with a mean structure incorporated.

To evaluate the model fit, the following criteria were evaluated: the Chi-Square value divided by the number of degrees of freedom (< 3), the comparative fit index (CFI > .90), the Root Mean-Square Error of Approximation (RMSEA < .06) with its 90% confidence interval (CI, lower bound < .05, upper bound < .10) (cf. Kline, 2005, p. 133ff.).

measurement of either the treatment perception or the mediating and dependent variable exists. Moreover, no systematic effects of attrition are assumed, because those who dropped out of the study after the initial survey do not differ from those who further participated in the study.

7.3. Results

This section investigates the relationship between routine media use and political support. The correlations between variables measuring media use, process perceptions, process preferences and political support are displayed in Table 7.1. The perceptions of political processes were significantly associated with political support in a way that both the perception of political processes as consensus-oriented and the perception of political processes as efficient are linked with higher levels of political support. Moreover, process preferences were significantly related to political support. Whereas high levels of consensus preferences are associated with high levels of political support, high levels of efficiency preferences are related to low levels of political support. Television use is significantly related to efficiency perception and efficiency preference. A high intensity of television use is associated with the perception of political processes as less efficient. A high intensity of television use is linked to stronger preferences regarding the efficiency of decision-making processes. There is no significant relationship between newspaper use and process perceptions or political support.

A variety of structural equation models were analyzed in order to test the assumptions formulated in Section 7.3.1. The analyses presented here are based on the sample of participants in the two treatment groups (n = 366).[95] Socio-demographic control variables (gender, age, education, political experience, and political ideology) were included in all of these models. In the interest of clarity, they are not displayed in the figures, however. Disturbances and error terms are omitted from the figures for clarity as well. Besides manifest variables (i.e. newspaper use, television use and exposure to stimulus articles) there are latent variables included in the models which are measured by several indicators in order to correct for measurement errors. The according measurement models are described in Appendix 10.3. In the figures, manifest variables are presented in squares and latent variables are presented in circles. Section 7.3.1 presents analyses of the role of routine media use as a predictor of political support. More precisely, the assumption that respondents' process perceptions mediate the impact of media use on political support is investigated. In addition, the media's impact on preferences regarding political decision-making processes and the discrepancy between preferences and perceptions is investigated (Section 7.3.2). In Section 7.3.3, the role of process preferences as a moderator of the impact of media on political support is analyzed. Section 7.3.4 presents

95 Because no measurement of respondents' article impressions exists for the participants in the control group, models that include the article impression variables are based on the sample of participants in the two treatment groups. In order to facilitate comparisons between the models, not only the models including the impression variables but also all other models are based on the sample of participants in the two treatment groups. Comparisons of results for models which are based on the sample with participants in the treatment groups (n = 366) with results for the same models based on the total sample (n = 523) show that the results differ only marginally (some path estimates differ slightly in the second digit after the decimal point).